1-1-1980

Priming processes in semantic memory.

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PRIMING PROCESSES IN SEMANTIC MEMORY

A Dissertation Presented

By

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Submitted to the Graduate School of the
University of Massachusetts in partial fulfillment
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

September 1980

Psychology

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DEDICATION

This thesis is dedicated with love and affection to

Laura S. Mahoney

and to the memories of

Robert F. Lorch

and

Kevin J. Mahoney

ACKNOWLEDGEMENT

I gratefully acknowledge the time and efforts of the members of my dissertation committee: Jim Chumbley, Lyn Frazier, Keith Rayner and Mike Royer. I would also like to acknowledge a particular debt of gratitude to Jerome L. Myers for his careful and unselfish guidance as the chairperson of my committee and as my teacher for six years.

ABSTRACT

Priming Processes in Semantic Memory

(September, 1980)

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How does the strength of an association determine the speed with which the association can be retrieved? Three alternative models of retrieval are developed within a network theoretic framework: Information is assumed to be represented in memory as a network of concept-nodes connected by labeled, strength-valued pathways. All of the models hypothesize a two-stage retrieval process consisting of an initial process of activation of associates of a concept-node, followed by a process of selection of activated pathways for evaluation. The Rate Model proposes that strength determines the rate at which a pathway is activated to some threshold required for selection; the Distance Model proposes that strength determines the amount of activation required to activate a pathway to threshold. Thus, both models hypothesize that strength influences the duration of the activation process and thereby the duration of the retrieval process. The Threshhold Model claims that the speed of activation of a pathway is indepen-

dent of strength, but that strong pathways are activated to a higher asymptote than weak paths and are consequently selected for further processing faster. Thus, the Threshold Model attributes strength effects to the speed of selection of a path, rather than to the speed of pathway activation.

Three priming experiments were conducted to discriminate the models. On each trial in Experiment 1, subjects were presented the name of a category (e.g., Animal) followed by a second word (e.g., Dog or Rose) and their task was to respond whether or not the second word was an exemplar of the category. RT to respond on positive trials was measured as a function of the interval between category and exemplar presentation (SOA) and as a function of the strength of the category-exemplar association. The SOA was assumed to provide a headstart on the activation process, but not to influence the selection process. Thus, the finding that SOA and strength of association had independent effects on RTs despite large effects on both variables was interpreted as support for the Threshold Model's claim that SOA and strength influence different stages of processing -- activation and selection, respectively. The results contradicted the common hypothesis of the Rate and Distance Models that the two variables both influence the activation process.

On each trial in Experiment 2, subjects were presented with a prime word followed by the name of an exemplar and their task was to say the exemplar word aloud as soon as they recognized it. Subjects were faster to say the exemplar when it was preceded by the name of its category than when it was preceded by the word "blank." Further, priming effects were greater when the category prime and exemplar probe were strongly associated than when they were weakly associated. In addition, priming effects increased linearly as SOA increased from 150 to 600 msec. The effects of SOA and strength of association were again independent, however. Thus, the results of Experiment 2 also provided support for the Threshold Model. A final priming experiment using a sentence verification task failed to produce any conclusive results.

The support for the Threshold Model provided by the results of Experiments 1 and 2 was interpreted as suggesting a fundamentally different conception of the activation process than has usually been assumed: Rather than being a mechanism for the retrieval of individual associative connections, the activation process appears to be a pre-processing mechanism that makes the entire set of associates of a concept simultaneously available for closer scrutiny by a selection mechanism.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER I

INTRODUCTION AND OVERVIEW

We remember some things more readily than we remember others. I am always able to recall the capitals of the two states that I have lived in, Connecticut and Massachusetts; I am generally, but somewhat less reliably able to recall the capitals of Vermont and New Hampshire; only on my best days can I recall the capitals of Montana and North Dakota and then only after a long period of thought. Note that these are all facts that I learned at one time and presumably still have stored in memory, but the ease with which I am able to retrieve these facts varies greatly. Such variations in the retrievability of information have frequently been attributed to variations in the "strength" of the corresponding memory "traces" (e.g., Anderson, 1976; Collins & Loftus, 1975; Wickelgren, 1976).

There is considerable experimental evidence from a variety of sources to corroborate the intuitive observation that some traces are stronger, or more firmly established in memory than other traces. For example, subjects consistently produce some words as associations to a stimulus word more frequently than they produce other words (e.g., Battig & Montague, 1969; Postman & Keppel, 1970); ideas that are more important to the coherence of a story or an argument presented in a text are better recalled than extraneous details (Johnson, 1970; Kintsch & van Dijk, 1978; Meyer, 1975); words or paired-associates or facts that are more frequently studied are better remembered than infrequently studied stimuli (e.g., Anderson & Bower, 1973; Nelson, 1977). The basis of memory trace strength will not be of direct concern in this paper; generally, trace strength appears to be complexly determined by the frequency of occurrence of the corresponding stimulus event (e.g., Anderson & Bower, 1973), by how well integrated the trace is with existing knowledge structures (e.g., Rosch, 1975; Smith, Adams, & Schorr, 1978), and by how recently the trace has been accessed in memory (e.g., Anderson & Bower, 1973; Perlmutter, Sorce, & Myers, 1976). What is of direct interest is the observation that traces which are available in memory vary in how accessible they are at any moment in time (Tulving & Pearlson, 1966); strong traces are generally more accessible than weak traces.

Strong traces are more accessible than weak traces in both the sense that it is more probable that they can be retrieved at a particular moment in time and in the sense that strong traces can be retrieved more rapidly than weak traces (Anderson & Bower, 1973; Waugh, 1970). It is the latter observation which is the focus of this thesis: Specifically, how does the strength of a memory trace determine the speed with which the trace can be retrieved from memory? This issue is developed more fully in the following section where a framework is presented for thinking about memory representation and retrieval.

Memory as an Associative Network

The representation of information in a network. Following several theorists (Anderson, 1976; Anderson & Bower, 1973; Collins & Loftus, 1975; Hayes-Roth, 1977), we will adopt the view that information is represented in memory as a vast network of concepts connected by associations. Such a hypothetical network representation is presented in Figure 1. According to this framework, concepts are represented as nodes in the network and relations between concepts are represented as associative pathways connecting concept-nodes. Two important characteristics of the associative pathways are: (1) associations are not undifferentiated, rather they are labeled with the appropriate conceptual relation; (2) associations vary in strength, which might be represented by the length of the associative pathway in the network. It is assumed that associations are bidirectional, but not symmetrical. For example, if the fact that "A dog is an animal" is learned, then this fact is accessible from either the "dog" or the "animal" concept-node. The strength of the "animal-dog" associative connection is not necessarily the same as the strength of the "dog-animal" association (Waugh, 1970), although it is probably the case that the strengths of the two associations are positively correlated. With these representational assumptions as a foundation, consider next how information in memory is processed.

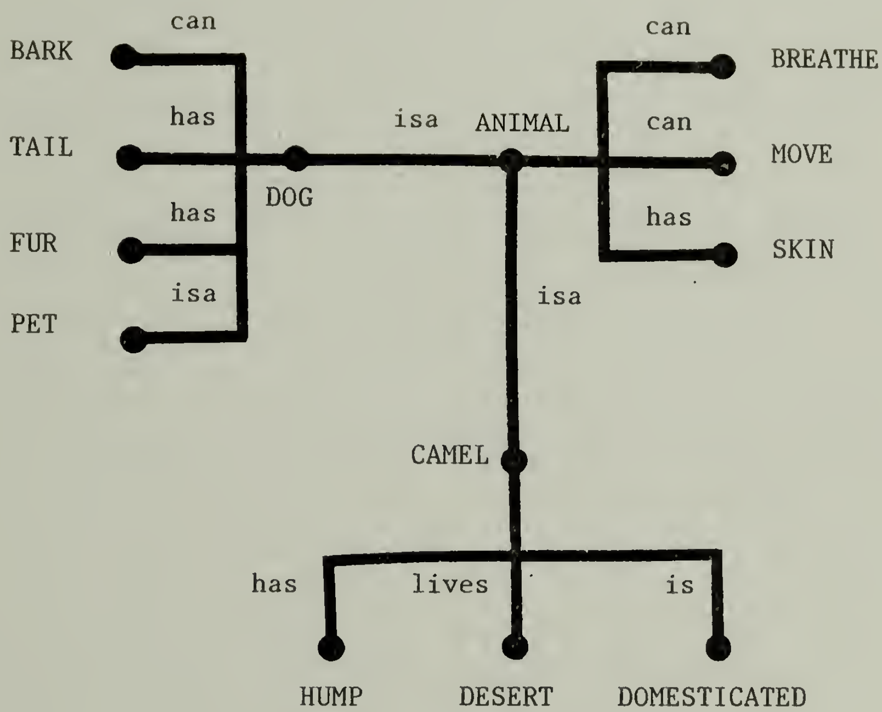

Figure 1. A hypothetical memory structure.

The retrieval of information from a network. The retrieval of information from memory is assumed to involve a limited capacity, two-stage process. The initial stage of retrieval consists of a search of the network structure. When a concept is "thought about", its corresponding node in memory is accessed and information about the concept is located by a search of the associative paths emanating from the concept-node. The search process itself is assumed to consist of a "spreading activation" process (Anderson, 1976; Collins & Quillian, 1969): When a concept-node is accessed and thus activated in memory, activation spreads in parallel from the concept-node down the associative pathways connected to the concept-node. Activation builds on the pathways to some limit as long as attention is on the concept. Since the accessibility of an associative connection is assumed to vary with its level of activation, the result of the activation process is that information about the attended concept increases in accessibility continuously over time to some limit.

The second stage of retrieval is a selection process. Given that many associations of a concept are activated during the search process, some mechanism is required to select each activated pathway to evaluate the nature of the information it represents. For example, given the task of producing an exemplar of the category "animal", the search process would first activate information about the concept "animal." Some of the concepts activated by the search process would be relevant to the task (e.g., "dog"; "camel"), but many would be irrelevant (e.g., "can move"). Thus, the selection process would perform the necessary function of isolating and evaluating each activated pathway individually to determine whether the retrieved information fulfilled the requirements of the task (in this case, to determine whether the retrieved associative pathway consisted of a category membership relation).

Strength effects on retrieval. We have considered a view of memory as a network of labeled associations varying in strength. Retrieval of information from the memory network is assumed to involve a two-stage process of activation and selection of associative connections. Within this framework, how does the strength of an association of a concept determine how rapidly the pathway will be retrieved? One possibility is that the strength of an association determines how rapidly that association will be activated. A second possibility is that it is not the activation process that is directed by strength, but the selection process. Yet a third possibility is that both the selection and activation process are strength-controlled. The concern of this paper is to distinguish these alternative models of how strength controls retrieval.

Organization of the Paper

In the following chapter, three models will be developed which differ in their claims about how strength controls retrieval. In Chapter III, data relevant to the evaluation of the models will be reviewed and a rationale for distinguishing the models will be presented. The subsequent three chapters will present three experimental tests of the models employing different, but related experimental tasks. The final chapter will summarize the results and conclusions from the experimental tests and discuss the implications of the findings for a model of retrieval.

CHAPTER II

THREE MODELS OF MEMORY RETRIEVAL

Three models of memory retrieval will be presented in this chapter. The models are distinguished by their explanations of how strength controls the retrieval of a memory trace. The first two models to be considered attribute strength effects to the operation of search processes during retrieval; the third model attributes strength effects to the mechanism which selects activated pathways for further processing. All of the models share certain assumptions consistent with the network theoretic framework within which they are developed. All three models assume that: (1) Activation of a concept-node resulting from attention to the concept initiates the activation of associates of the concept. (2) As long as the concept continues to be processed, activation summates on associative pathways over time causing the pathways to become increasingly available to subsequent cognitive operations. Thus, it is assumed that the (possibly incomplete) output of a processing operation is continuously available to other processes (McClelland, 1979; Norman & Bobrow, 1975), although some ceiling on availability is eventually reached. (3) Finally, it is assumed that the processing time required to select an activated pathway for further processing depends upon the activation level of the pathway; the higher the activation level of the connection, the less time it will take to select the path for evaluation. The models are distinguished by their assumptions concerning whether strength affects the resting level of activation of a pathway, whether strength affects the asymptotic level of activation of a pathway, or whether strength affects the rate of activation of a pathway during processing. The distinctions between the three models are considered below in some detail.

Search Models

One way in which strength could affect retrieval is by controlling the activation process which locates information in memory. Two alternative mechanisms are possible: (1) Strength may directly determine the rate at which an associative pathway is activated, with strong pathways being traversed at a faster rate than weak pathways; (2) Alternatively, strength may determine how much activation is required to fully activate an associative pathway. These two models are developed below.

The Rate Model.

General description of the Rate Model. The defining assumption of the Rate Model is that strength of association controls the allocation of processing capacity during memory search, with strong associative paths receiving more activation per unit of time than weak paths. It is important to note that "rate" is intended in its usual sense of amount of activation allocated per unit of time. It is further assumed that neither the resting level of activation nor the asymptotic level of activation of an associative pathway depends upon strength. Since the total amount of activation allocated to a path is independent of strength, strong pathways are activated to asymptote faster than weak pathways because of their different activation rates. It is assumed that when a pathway is activated to some threshold level, it is selected for any subsequent processing. Thus, strong associative paths will be retrieved faster than weak paths because they will be activated at a faster rate. An idealized version of the Rate Model's prediction of the relationship between the amount of time spent processing an association and the level of activation of the pathway is shown as a function of the strength of the association in panel A of Figure 2. To summarize, activation increases at different rates to the same asymptote for strong and weak associations. Having formulated a general version of the Rate Model, let us next consider a specific version of this class that is presented in the literature.

The ACT Model. Anderson (1976) has presented a theory of memory that is quite consistent with the general framework employed in this paper. The retrieval of information in ACT consists of a two-stage process of search and selection. In the initial search stage of retrieval, information is activated and thus made available to influence further processing operations. Search consists of a strength-controlled spreading activation process. Given an active node, *x*, in memory and some nonactive link, *l*, connecting *x* and *y*, then the probability that link *l* will be activated in the next unit of time is:

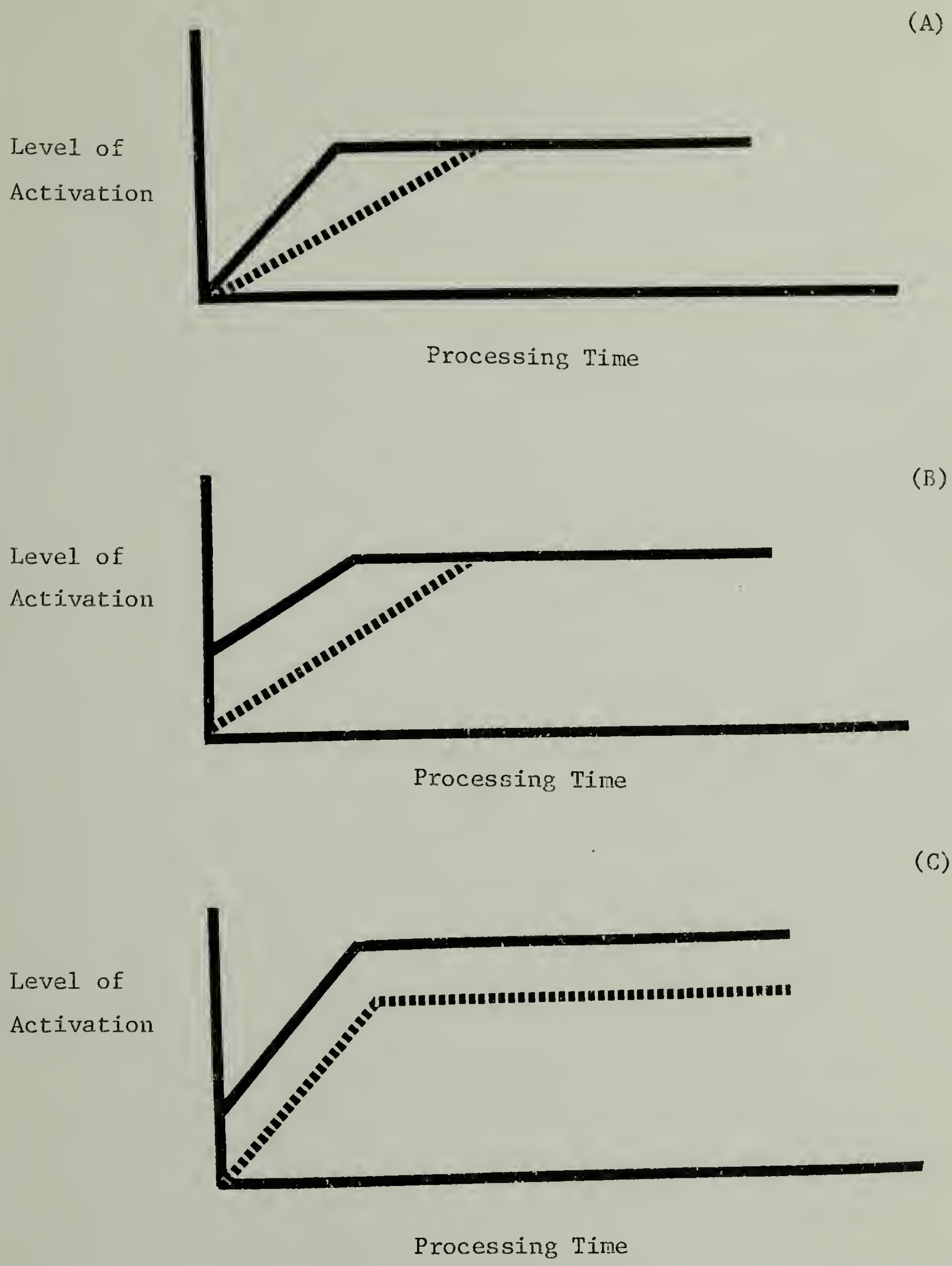

Figure 2. Predicted relationships between processing time and level of activation as a function of strength of association. Predictions are presented separately for the Rate Model (A), Distance Model (B), and Threshold Model (C). Solid lines indicate a strong association and dashed lines indicate a weak association.

$1 - \underline{e}^{-s/aS}$; where $\underline{s}$ is the strength of link $\underline{l}$, $\underline{S}$ is the total strength of all links attached to node $\underline{x}$, and $\underline{a}$ is a time scale parameter reflecting the rate of spread of activation. Thus, the greater the proportional strength of a link, s/S, the greater its probability of activation will be in any unit of time. Note that activation in this model is presumed to be all-or-none rather than continuous. Discriminating between these two versions of the general model would be difficult, if not impossible, however, because the necessity of averaging performances across subjects and stimulus materials in experiments obliterates the most direct evidence relevant to the all-or-none vs. continuous distinction.

Once a memory structure is activated, a "production" is selected which directs further processing operations. The activation of some structure in memory constitutes the necessary condition for the selection and activation of an appropriate production; thus, the activation of a memory structure actually selects the next structure to be activated in memory.

In addition to the ACT model, there are several other competitive-search models in the literature (Collins & Loftus, 1975; Hayes-Roth, 1977; Perlmutter, Harsip, & Myers, 1976; Note 1). The Collins and Loftus and the Hayes-Roth models do not specify the nature of the retrieval mechanism beyond the proposal of a competitive-search process, while the parallel search process hypothesized by Perlmutter et al., is equivalent to ACT's activation process. Thus, the ACT model serves as a prototypical example of a Rate Model: Variations in speed of retrieval are attributed to strength-determined variations in the rate of pathway activation. An alternative hypothesis about how strength influences the search process is considered next.

The Distance Model.

General description of the Distance Model. The defining assumption of the Distance Model is that strength determines the amount of processing that an association requires in order to reach a given level of accessibility, but strength does not direct the allocation of activation. A convenient way to think about this model is presented in Figure 3, where a strong association is represented as a short pathway in memory and a weak association is represented as a long path. Within this framework, activation must travel a longer distance to fully activate a weak association than to fully activate a strong association. The important assumptions of the Distance Model are as follows. First, the asymptotic activation level of a pathway does not depend upon strength. The resting level of activation of a pathway does, however, depend upon strength; strong paths have higher resting levels of activation than weak paths. Thus, it takes less activation to activate a strong associative pathway to asymptote than to fully activate a weak association. Finally, the rate of activation of a pathway is independent of strength. Since activation rate does not depend upon strength but the amount of activation required to fully activate a pathway is inversely related to strength, it will take longer to fully activate a weak pathway than a strong pathway and retrieval time will consequently be longer for weak associations than for strong. When a pathway is activated to some threshold level, it is selected for evaluation and retrieval is completed for that association.

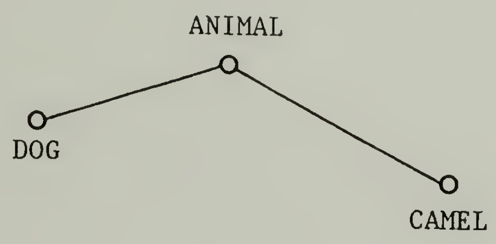

Fig. 3. Representation of a strong (Dog-Animal) and a weak association (Camel-Animal) according to the Distance Model.

An idealized version of the Distance Model's prediction of the relationship between the amount of time spent processing an association and the activation level of the pathway is shown as a function of the strength of the pathway in panel B of Figure 2. Three important claims of the model are represented in Figure 2: First, weak associations have a lower resting level of activation than strong associations, as represented by the lower intercept for the weak association function. Second, in a given unit of processing time, the increases in activation are the same for strong and weak pathways as long as activation is below asymptote; this is represented by equivalent slopes for the rising portions of the two functions in panel B. Finally, the asymptotic activation level of a pathway does not depend upon its strength. Comparing panels A and B, note that the Rate and Distance Models differ in their claims about how strength affects the resting level of activation of a pathway and about how activation increases over time as a function of strength.

Having formulated a general version of the Distance Model, let us now consider three examples of this class of models. An interesting observation about the first two models to be discussed is that they both make strong claims concerning the basis of strength: The HAM model (Anderson & Bower, 1973) claims that all strength effects can be reduced to a recency principle; Landauer's (1975) model attributes all strength effects to a frequency or recency principle. Since the basis of strength is not at issue, however, we will not consider this point further. The third model to be presented is the logogen model (Norton, 1969; 1970). The logogen model is restricted in that it is a model of word recognition; however, a straightforward adaptation of the model to the domain of processing of associative relations will be developed.

The HAM model. The HAM model (HAM is an acronym for "Human Associative Memory") was presented in 1973 by Anderson and Bower. HAM is the predecessor of ACT and, as such, bears many similarities to ACT. There are some major differences, however, in the search mechanisms of the two models.

The search for information about a concept is controlled in HAM by: (1) the kind of information desired about the concept; and (2) the recency with which the desired information was processed. It is useful to conceptualize the search process as a serial scan of a list structure, as Anderson and Bower suggest; this way of thinking about HAM's search process emphasizes the model's close ties to category-search models (e.g., Freedman & Loftus, 1971; Juola & Atkinson, 1971; Landauer & Meyer, 1972) and demonstrates that such serial scan models may be properly considered exemplars of the general class of distance models. The retrieval mechanism works as follows: When a request for information about a concept is presented, a list of appropriately-labeled, recency-ordered associations of the concept-node (called a "GET-list") is retrieved and searched. The search process consists of a serial scan of the contents of the GET-list. According to this search mechanism, strong paths have a higher resting level of activation than weak paths in the sense that they are higher in the GET-list and will consequently be located sooner. The rate of activation of an association does not depend upon strength, however: Given two associations differing in their location on the GET-list, the scan process will advance the same distance down the list towards both associations in any unit of time. Finally, when the scan process has located a particular association on the GET-list, the pathway is selected and evaluated by a MATCH process which determines its relevance to task demands. Once an association is located by the search process (i.e., activated to threshold), the speed with which the MATCH process evaluates the pathway does not depend upon its position in the GET-list (i.e., does not depend upon its strength).

<u>The random storage model</u>. Landauer (1975) has proposed a model of memory that is intriguing for its ability to account for some important

memory phenomena with minimal assumptions about representation and retrieval. The memory structure of the model consists of a large three-dimensional space containing a very large number of small storage loci that are homogeneously distributed throughout the space. The amount of information that can be stored in a single locus is assumed to be variable and what the stored information represents is also a variable. In any given interval of time, data may be entered into the storage location currently indicated by a "pointer." The pointer moves slowly in a random walk through the memory structure such that the location of a particular datum relative to another approaches independence as the time between the two acts of data entry becomes sufficiently long. The only source of nonrandomness in the data entry mechanism, then, arises from the fact that if the time between two data entries is short, their corresponding storage loci will be near one another.

Of particular interest is the retrieval mechanism of the random storage model. Information is accessed in memory by an undirected search process. When some information is desired from the memory system, a search is initiated from the pointer's current location. The search proceeds in all directions in an expanding sphere up to some radius limit. The rate of spread of this activation process outward from its starting location is constant; thus, the search process is serial with respect to locations differing in distance from the search origin, but the search is parallel with respect to locations at the same distance from the origin. An unspecified selection mechanism is assumed to recognize sought-after information when it is activated by the search process.

Given the retrieval mechanism of the random storage model, the determinant of how long it will take to retrieve some particular information from memory is the distance to the pointer from the nearest location containing the target information. Two factors will affect how far the pointer is from a location containing some particular information: (1) how much time has passed since the target information was entered into a memory location; and (2) how frequently the target information has been processed. The more recently the target information has been processed, the nearer its corresponding memory location should be to the pointer; the more frequently the target information is processed, the more memory locations it will be represented in and thus the closer it should be -- on the average -- to the pointer.

Despite its radical form, the random storage model exhibits the important characteristics of a Distance Model. As in HAM, more recent/frequent information has a higher resting level of activation than less recent/frequent information in the sense that it is most probably located nearer to the pointer, where search originates. The rate of the search process is a constant and, in particular, does not depend upon the contents of any of the memory locations accessible from the pointer. Finally, when a memory location containing searched-for information is found, that information is selected and recognized by a process which does not depend upon the recency or frequency of processing of the information.

The logogen model. Morton (1970) has developed an influential model of word recognition which serves as an excellent exemplar of a Distance Model. An outline of Morton's model will be presented, then the basic model will be adapted to the present domain of consideration.

A logogen is a memory structure defined by its output, which can be represented by sets of visual, acoustic, phonological and semantic attributes. Loosely speaking, a logogen may be thought of as corresponding to a word. A logogen is a counting device that is incremented whenever any of its defining attributes is input to the Logogen System, regardless of the source of the input. When the count of a logogen exceeds a certain critical value, the corresponding response is made available. For example, when presented with a stimulus in a word recognition task, the subject's response will correspond to the first logogen to be activated to its threshold. An important determinant of a particular logogen's threshold is the frequency of usage of the logogen; frequently activated logogens will have lower thresholds than infrequently activated logogens. Finally, it is assumed that sensory analysis of a stimulus generally proceeds without reference to subsequent parts of the system and the results of such analysis are available to the whole Logogen System. Following Schuberth and Eimas (1977), it is assumed that the rate and extent of sensory processing is a function of stimulus factors alone and, in particular, does not depend upon the strength of the logogen.

Consider how the logogen model may be adapted to the present domain of concern. First, corresponding to the logogen, the association between two concepts is assumed to be a counting device that keeps track of the amount of activation on the pathway. When a concept is accessed in memory, activation spreads from the concept-node and each associative link "counts" units of activation and signals its availability when the count reaches some threshold value. The strength of a given path is represented in its resting level of activation or, equivalently, in the number of units of activation required to reach threshold. At threshold, all associative links are assumed to be equally available. Finally, it is assumed that the rate at which units of activation accrue in an associative link is independent of the strength of the link.

Summary. Three exemplars of the Distance Model have been discussed. Although the models differ drastically in many respects, they share some assumptions about the search process which results in their common classification. All of the models propose that the activation process proceeds at a constant rate, but that more activation is required to activate a weak path to threshold than to fully activate a strong path.

Selection Models

An alternative to the proposal that strength controls the activation process is the hypothesis that strength controls how rapidly information is selected for evaluation after it has been fully activated by the search process. A general description of this class of models is presented below, then an example of the general class is discussed.

The Threshold Model.

General description of the Threshold Model. The central claim of the Threshold Model is that strength controls retrieval by determining how quickly a pathway is selected for evaluation. The model claims that the search process requires the same amount of time for all associative pathways regardless of strength; all pathways receive the same amount of activation at the same rate. While activation rate does not depend upon strength, the initial resting level of activation of a pathway does depend upon strength. Further, since all pathways receive the same increment in activation level as a result of search, pathways differ in asymptotic activation levels as well as in resting levels. Because it is assumed that speed of selection depends upon activation level, strong paths will be selected and thus retrieved faster than weak paths because of their generally higher levels of activation. The Threshold Model's prediction of the relationship between the amount of time spent processing an association and the level of activation of the association is shown as a function of the strength of the association in panel C of Figure 2. The claims of the Threshold Model can be readily contrasted with the corresponding hypotheses of the Rate and Distance Models by comparing panel C with panels A and B, respectively.

A theory of retrieval dynamics. Wickelgren (1976) and his colleagues (Corbett, 1977; Corbett & Wickelgren, 1978; Dosher, 1976) have outlined a network strength theory which represents more a framework for theorizing rather than a specific theoretical commitment. One straightforward version of the theory provides an example of a Threshold Model, however.

The search mechanism of Wickelgren's theory consists of an unlimited capacity, parallel activation process. Thus, when a concept-node is accessed in memory, its associates are searched in parallel and the speed of activation of a given association does not depend upon the number or distribution of other associates of the concept-node from which the search originates. The speed with which a link is activated to asymptote does not depend upon the strength of the associative link; rather, strength determines the asymptotic level of activation of a pathway, with strong paths having a higher level of activation than weak paths. The activation level of an association will, in turn, determine the probability and speed with which the pathway can be recovered by the selection process. A useful analogy is provided by pandemonium models (e.g., Neisser, 1967): Strong associations "cry out louder" for selection than weak associations. (Note that Wickelgren does not state whether the resting level of activation of a pathway depends upon strength, but the important observation is that the speed of activation to asymptote does not depend upon strength.)

General Summary

Three models of retrieval have been developed and specific exemplars of each class have been presented in this chapter. Two of the models hypothesize that the strength of an association determines how rapidly that pathway will be activated during search; the Rate Model claims that strength determines the rate at which an associative pathway is activated, while the Distance Model proposes that strength determines how much activation will be required to activate a pathway to a threshold for selection. In contrast to the search models, the Threshold Model hypothesizes that the activation process is unaffected by strength, but the process of selecting an activated association is faster for strong associations because strong associations are activated more during search than weak associations. The varying claims of these three models are summarized graphically in Figure 2.

CHAPTER III

TESTS OF MODEL SUFFICIENCY AND RATIONALE FOR DISCRIMINATING THE MODELS

Having developed three models of memory retrieval and considered examples of each in the preceding chapter, the present chapter will focus on the empirical literature relevant to an evaluation of the models. The theoretical sufficiency of the models will be examined in the first half of the chapter, while a rationale for empirically discriminating the theoretical positions will be developed in the second half of the chapter.

Tests of Model Sufficiency

The effect of strength on the speed of memory retrieval. The Rate, Distance, and Threshold Models all make the general prediction that strong associations will be retrieved faster from memory than weak associations. According to the Rate and Distance Models, the stronger an association is, the faster it will be activated by the search process and thus the faster it will be selected and retrieved. The search process will activate strong and weak associations equally quickly according to the Threshold Model, but strong associations will be activated to a greater degree with the result that they will be selected sooner than weak associations for subsequent processing. There is ample evidence from a variety of sources to confirm this general prediction.

<u>Strength effects on recall latency in episodic memory tasks</u>. Paired-associate recall experiments provide one source of support for the prediction that strength of association influences the speed of retrieval. In a typical experiment, subjects are presented pairs of words for study and their task is to learn to associate the two words in each pair on the study list. On each trial during the testing phase of the experiment, subjects are presented the first word of a previously studied pair and they are required to respond with the second word of the pair; latency to produce the second, response word is the dependent variable of interest. Waugh (1970) has demonstrated that the response latency to a given paired-associate decreases as the number of tests on the item increases; this decrease in response latency continues even after recall accuracy has reached 100% for the list. On the assumption that the strength of a paired-associate increases with repeated testing, Waugh's results confirm the prediction that retrieval latency decreases as strength increases. A similar effect of number of tests on paired-associate recall latency has been reported by Perlmutter, Sorce, and Myers (1976). Finally, Perlmutter et al., also found that recall latencies were shorter to paired-associates that were pre-experimentally associated (e.g., King-Crown) than to paired-associates that were pre-experimentally unassociated (e.g., Train-Church). On the assumption that the pre-experimental associates were more strongly associated than the non-associates, this result also confirms the general prediction of faster retrieval with greater memory strength.

<u>Strength effects on recall latency in semantic memory tasks</u>. The analog of the paired-associate task in the semantic memory literature is the production task (e.g., Freedman & Loftus, 1971). On each trial in a production task, subjects are presented with the name of a semantic category and a letter- or adjective-restrictor (e.g., Animal-D or Bird-Yellow). The subjects' task is to produce an exemplar of the category that begins with the letter-restrictor (e.g., Dog) or that has the property designated by the adjective-restrictor (e.g., Canary); as usual, the subjects' latency to produce an appropriate exemplar is the dependent variable of interest. The consistent finding in these experiments has been that subjects are faster to respond the more strongly associated the targeted exemplar is with respect to the semantic category (Freedman & Loftus, 1971; Loftus, 1973; Loftus & Suppes, 1972; Loftus & Loftus, 1974). For example, subjects are faster to respond "Robin" to "Bird-R" than they are to respond "Canary" to "Bird-C." Strength of association is typically operationally defined as the percentage of subjects producing a given exemplar in response to the semantic category in a constrained association task (e.g., Battig & Montague, 1969). Thus, the findings from both episodic and semantic recall experiments converge on the conclusion that strength of association influences the speed of memory retrieval, as predicted by the three models.

<u>Strength effects on recognition latency in episodic memory tasks</u>. Anderson (1976) has examined the effects of associative strength on recognition latency in a fact retrieval task. In a typical experiment,

subjects learn a list of sentences of a common form such as "A person is in the location." After learning the list of episodic facts to some recall accuracy criterion, subjects are then tested for their recognition of the facts. In the testing phase, subjects are presented either entire sentences or combinations of the major content words from the list of facts and their latency to classify each test probe as an "old" or "new" sentence or word combination is measured. Distractors are typically constructed by re-pairing the content words from old facts. One important result from these experiments is that subjects are faster to classify a fact as "old" the more often the fact has been tested. Again, on the assumption that the strength of the fact's representation in memory is incremented with repeated testing, this result is consistent with the claim that speed of retrieval increases as strength increases.

Strength effects on recognition latency in semantic memory tasks. The sentence verification task is the semantic memory analog of the fact retrieval task. In this task, subjects are presented with simple assertions (e.g., "A canary is yellow") and their task is to classify each statement as "true" or "false"; the latency to verify each sentence is the dependent variable of interest. The results from this literature are generally compatible with the findings from fact retrieval experiments. First, subjects are faster to respond "true" the stronger the association is between the subject- and predicate-word of the sentence (Ashcraft, 1978a; Collins & Quillian, 1969; Conrad, 1972; Loftus, 1973; Rips, Shoben, & Smith, 1973; Rosch, 1973;

Sanford, Garrod, & Boyle, 1977; Sanford & Seymour, 1974a; 1974b; Schaeffer & Wallace, 1969, 1970; Wilkins, 1971). For example, subjects are faster to verify that "A robin is a bird" than they are to verify that "A canary is a bird." This result holds regardless of which of several, highly-correlated measures of strength of the subject-predicate relationhip is employed (e.g., production frequency; ratings of subject-predicate "relatedness"; ratings of strength of association).

The effects of strength of the verification of false sentences appear to challenge the prediction that retrieval time decreases as associative strength increases: negative responses are usually slower when the subject- and predicate words are strongly associated than when they are weakly associated (Collins & Quillian, 1972; Gellatly & Gregg, 1975; 1977; Homa & Silver, 1976; Kunzendorf, 1976; Meyer, 1970; Sanford et al., 1977; Schaeffer & Wallace, 1969; 1970). Several observations resolve this apparent contradiction. First, the result may well reflect the operation of decision strategies as opposed to retrieval processes during sentence verification. Typically, the manipulation of the strength of the subject-predicate relation for false sentences consists of comparing sentences in which the subject and predicate are moderately associated (e.g., A bat is a bird) with sentences in which the two words are unrelated (e.g., A gun is a bird). This procedure confounds sentence truth-value with the strength of the subject-predicate association; strongly associated sentences are invariably true and weakly associated sentences are false. The result of this confounding is that subjects are able to classify sentences as true or false merely by assessing the strength of the subject-predicate relationship, rather than by analyzing the nature of that relationship (Smith, Rips, & Shoben, 1974; Smith, Shoben, & Rips, 1974). A second observation is that it is not necessarily the strength of the subject-predicate relation that should predict performance on false sentences, according to the models under consideration. Rather, the strength of the association(s) which contradicts the stimulus sentence should be the primary determinant of response time. For example, if the sentence to be verified is: "All animals are dogs", then a critical determinant of response latency should be the strength of a counterexample to the sentence (e.g., Some animals are cats). When experimenters have taken care to identify the types of information that may be used to reject false sentences in a sentence verification task, they have consistently found that as the strength of contradictory associations increases, the latency to respond "false" decreases (Anderson & Reder, 1974; Glass, Holyoak, & Kiger, 1979; Glass, Holyoak, & O'Dell, 1974; Holyoak & Glass, 1975; Lorch, 1978; Note 2). With these observations in mind, it seems reasonable to conclude that as the strength of an association sufficient to determine a "true" or "false" response increases, the latency to verify a sentence decreases.

Summary. The Rate, Distance and Threshold Models all propose that associative strength orders the retrieval of information about a concept in memory. According to the Rate and Distance Models, the strength of an association determines how quickly the association will be located or activated by the search process; the Threshold

Model, on the other hand, attributes strength effects to the speed with which an association will be selected for further processing after it has been activated. The evidence reviewed to this point does not discriminate the locus of strength effects on retrieval -- search or selection, but it does demonstrate the sufficiency of all three models to handle an important empirical result: The findings from both semantic and episodic memory paradigms employing both recall and recognition tasks all support the general prediction of the models that speed of retrieval of an association increases as the strength of an association increases.

The effect of associative interference on the speed of memory retrieval. While it is true that associative strength will determine the speed of retrieval of an associate when other factors are held constant, strength should not be the sole determinant of retrieval time. Because all three models assume that retrieval processing capacity is limited, they make the common prediction that the time required to retrieve a particular associate of a concept will depend not upon strength *per se*, but upon the strength of the associate relative to the strengths of all other associates of the concept that are competing for processing capacity. The three models differ with respect to what they see as the nature of processing limitations on retrieval. All of the models assume that the selection process represents a bottleneck during retrieval, but the models propose different mechanisms for dealing with the limitations of the selection process. Various exemplars of the Rate Model propose that a given associate commands a percentage of the available activation according to the percentage of total associative strength it represents (Anderson, 1976; Perlmutter et al., 1976). Thus, the relative strength of an association is the important determinant of how rapidly the association will be selected. Similarly, the order of selection of pathways for evaluation is determined by their relative strengths according to the Distance Model (Anderson & Bower, 1973). Finally, although the Threshold Model hypothesizes that the speed of activation of an association is independent of its strength, the model proposes that the order of selection of an association for evaluation depends upon its level of activation relative to the activation levels of all other pathways competing for selection. Since activation level depends upon strength, the Threshold Model also generates the prediction that the distribution of strengths of associates of a concept will be an important determinant of the time required to retrieve a particular associate of the concept. In fact, there is substantial evidence from a variety of episodic memory experiments to confirm this prediction.

Interference effects on recall latency in episodic memory tasks. Perlmutter, Harsip, and Myers (1976) have provided two demonstrations that irrelevant associates of a stimulus word interfere with retrieval of the appropriate response word in a paired-associate recall task. In the first of two experiments, subjects learned a twelve-item list of paired-associates. The stimulus words of the PAs varied in frequency of English language usage and in "meaningfulness" (i.e., number of free associations which could be produced to the word in a limited time interval). The frequency manipulation was presumed to represent a manipulation of the sum of the strengths of pre-experimental associations of the stimulus word; the meaningfulness manipulation was interpreted as a manipulation of the number of pre-experimental associates of the stimulus word. The finding that subjects were 150 milliseconds slower to recall the appropriate response word when the stimulus word was high in frequency than when it was low in frequency thus supports the prediction that retrieval time depends not only upon the strength of the target association, but also upon the strengths of other, irrelevant associates of the stimulus. There was also a tendency for recall to be slower when the stimulus word was low in meaningfulness than when it was high (50 msec), but the effect was not reliable.

In the second paired-associate experiment, the stimulus words varied with respect to whether their primary associate was a relatively frequent or relatively infrequent free associate. The results were that subjects were slower to respond with the appropriate episodic association to a stimulus word with a frequent primary associate. Again, the distribution of strengths of pre-experimental associates of the stimulus word influenced the time it took to retrieve the appropriate response.

Interference effects on recognition latency in episodic memory tasks. There are several demonstrations that the latency to classify an item as "old" or "new" in a fact retrieval paradigm depends upon the number of facts learned about constituent words in the probe item. A prototypical example of the "fan effect" is provided by Anderson (1974; Anderson & Bower, 1973). Subjects studied sentences of the form: "A _person_ is in the _locaction_" (e.g., "A hippie is in the park"). A given person (e.g., hippie) or location (e.g., park) could appear in one, two, or three sentences; thus, there were nine different conditions determined by the nine different sentence-types that could be formed by orthogonally manipulating the number of sentences that shared a particular person or location. Each subject studied sentences representing each of the nine conditions. After learning the list of sentences, subjects were presented the sentences for recognition. Distractors for the recognition task were constructed by randomly interchanging the person and location words of old sentences. The critical result was that subjects were slower to classify an old or new sentence as the number of sentences that shared the person or location of the probe sentence increased. Since subjects had received equal study time on all sentences, this result is attributable not to differences in the memory strength of each proposition but solely to differences in the number of propositions which were related by common sentence constituents. This finding has been replicated several times (Anderson, 1974; 1975; 1976; Anderson & Bower, 1973; Hayes-Roth, 1977; King & Anderson, 1976; Lewis & Anderson, 1976; Moeser, 1979; Reder & Anderson, in press; Shoben, Wescourt, & Smith, 1978).

While the fan effect appears to be a robust phenomenon, there are indications that such interference effects may be minimized or even eliminated under some conditions. One such condition may be overlearning. Hayes-Roth found that although fan effects were present initially in a fact retrieval experiment, the interference effects had disappeared by the nineteenth recognition test on the set of thirty facts. There were some peculiarities in her procedure which raise doubts about the generality of her findings, however. Specifically, the distractors evidently remained the same throughout the experiment, creating what Shiffrin and Schneider (1977; Schneider & Shiffrin, 1977) have termed a "consistent mapping" condition. Shiffrin and Schneider have demonstrated that when a given stimulus is consistently associated with the same response and the association is extensively practiced, responding eventually becomes automatic (i.e., immune to interference). Thus, it is likely that subjects in Hayes-Roth's experiment did not have to evaluate the sentences at a "semantic" level in order to determine whether they were new or old; rather, it would have been sufficient to encode the subject-verb-object (SVO) sequence and associate it with the appropriate response. Related to the point that sentences were probably evaluated in a superficial way is an observation about the procedure used to construct distractors. Distractor sentences were constructed by either reversing the S and O words of old sentences or by replacing the S, V, or O of an old sentence with the S, V, or O of one of six filler propositions. This procedure may have allowed subjects to develop a very superficial processing strategy to do the recognition task. For example, subjects could have identified a probe sentence as "new" by recognizing that the initial constituent of the probe was the object constituent of an old sentence or by recognizing that a constituent of the probe came from one of the six filler sentences. A final criticism is that old and new sentences were yoked in pairs such that the sentences in a pair were closely related. Perhaps the similarity of the paired sentences was sufficiently great that the task reduced to one of first recognizing which of the thirty sentence-pairs was being tested on a trial, then determining which sentence in the pair was being presented. Again, such a strategy would eliminate fan effects.

Another possible condition under which interference effects may be minimal is when the related facts are well-integrated. This situation has been examined by a couple of investigators (Moeser, 1979; Smith, Adams, & Schorr, 1978). In the initial phase of the Smith et al. experiment, subjects learned pairs of sentences that shared the same subject noun, but which were unintegrated. For example, one sentence pair was: "Marty broke the bottle" and "Marty did not delay the trip". In the second learning phase of the experiment, subjects studied a third sentence which either did or did not integrate the pair it was presented with. For example, the integrated and unintegrated sentences associated with the preceding example were, respectively: "Marty was chosen to christen the ship" and "Marty was asked to address the crowd". In the final phase of the experiment, subjects were tested for their recognition of the learned sentences. The critical result in each of three experiments was that the latency to recognize a sentence from an integrated triple as "old" was no longer than the latency to recognize an old sentence from a control (unintegrated) pair of sentences (i.e., there was no fan effect for the integrated triple); subjects were slower to recognize an old sentence from an unintegrated triple than from a control pair. As in the case of the Hayes-Roth study, however, Smith et al.'s failure to find a fan effect in the integrated triple condition may be attributable to a procedural artifact. Specifically, the procedure for constructing the distractors for the recognition test allowed subjects to respond to an old probe from an integrated triple merely by assessing that the probe was consistent with the theme of the triple, thus bypassing the need for a more analytical assessment of whether the particular probe sentence was "old." In fact, Reder and Anderson (in press) have demonstrated that when the distractors are carefully constructed to force complete processing of every probe, large fan effects result even in the integrated triple condition. The nature of the Moeser (1979) demonstration that integration minimizes interference is similar to that of Smith, Adams, and Schorr and is susceptible to the same criticisms.

To conclude, while it seems certain that cognitive mechanisms exist which counteract interference effects, current attempts to demonstrate such mechanisms are inconclusive. What is clear is that interference effects do occur under a variety of conditions in an episodic recognition task. The existence of such interference effects indicates that the time it takes to retrieve a given associate of a concept depends not only upon the strength of that associate, but also upon the distribution of strengths of other associates of the concept.

<u>Interference effects on speed/accuracy tradeoff functions</u>. One

final source of evidence concerning the existence of interference effects on recognition latency comes from experiments employing SAT analyses. Dosher (Note 3) had subjects learn sets of three paired-associates, where interference sets were of the form: AB, DE, AC; while independent sets were of the form: AB, DE, FC. After learning the set for a trial, the subject was given a recognition test in which the probes consisted of the learned PAs or a recombination of the stimulus and response terms of the learned PAs. The testing procedure was to present the probe PA, then give a response signal at a lag of from 300 to 3000 milliseconds. The subject's task was to verify whether the presented item was an old or new PA within 200 milliseconds of the response signal. A d' measure of accuracy was plotted as a function of retrieval time (lag plus mean response latency) for each condition separately for each subject. The data were fit by exponential approach-to-limit models which differed in the number of free parameters they allowed. Models allowing the asymptote parameter and either of the retrieval parameters (time-intercept or rate) to vary freely provided a better fit to the data than a model allowing variation only in the asymptote parameter: Retrieval was slower in the interference condition than in the independence condition. A similar result occurred in an SAT experiment conducted by Wickelgren and Corbett (1977). Thus, the findings from the SAT paradigm are consistent with the results from reaction time studies: In all cases considered, subjects have been found to be slower to retrieve a given associate to some stimulus when other associates of the stimulus are also available.

Summary. Much literature has been reviewed which substantiates two important predictions of the models under consideration: (1) The time it takes to retrieve some association decreases as the strength of the association increases; and (2) The time it takes to retrieve some association also depends upon the distribution of strengths of other associations of the stimulus. The Rate, Distance, and Threshold Models all propose -- albeit with different mechanisms -- that the retrieval of associates of a concept is strength-determined; thus, they all account for the first finding cited above. Further, each model accounts for the existence of interference effects by the general assumption that retrieval processing capacity is limited. Thus, the findings reviewed in the preceding pages provide a general demonstration of the theoretical sufficiency of the three models.

Discriminating the Models: Isolating the Search Process

The Rate, Distance, and Threshold Models all incorporate mechanisms which explain the effects of associative strength and interference on retrieval time. The models are distinguished, however, by their accounts of how strength affects memory search. Thus, one way to discriminate between the models empirically is to isolate the activation process and examine its characteristics. The varying claims of the three models about how strength affects activation over time are summarized in Figure 2 on page 11. At hand, then, is the issue of how to empirically isolate the activation process.

The priming paradigm. The priming paradigm is ideally suited to the task of examining the activation process. Its basic structure is as follows. On each trial, the subject is presented first with a priming stimulus and then with a probe stimulus. The prime may be a sentence, a word, a row of asterisks, etc., and the subject may or may not be required to respond overtly to the prime. The probe may also be any of several possible stimuli and the subject is required to respond overtly to the probe. The experimenter's interest is in the subject's performance on the probe task as a function of the priming condition. Typically, performance is examined as a function of the relation between the prime and probe and as a function of the interval between prime and probe presentation, or stimulus onset asynchrony (SOA). As an example, the priming paradigm has often been employed to study word recognition. On each trial in a prototypical experiment, the subject is first presented with a prime consisting of a word or a row of asterisks, then is presented with a string of letters which must be classified as a word or nonword (e.g., Neely, 1977). RT to respond correctly to the probe when it is a word has been examined as a function of such variables as: the semantic relation of the prime and probe word; the orthographic or phonological similarity of the prime and probe word; whether or not the prime word validly predicts the nature of the probe; the amount of time the subject has to use the prime to prepare for the probe, etc.

The rationale of the priming paradigm is straightforward. If the prime's memory structure includes associations (pathways and nodes) relevant to the processing of the probe, then processing of the prime should influence performance on the probe task. Given an associative pathway connecting a prime and probe concept, then the stronger the association and the more time the subject is given to process the prime, the more the probe's memory structure should be activated by the prime. If it is assumed that RT to respond to the probe is a monotonic decreasing function of the level of activation of the probe's memory structure, then RT will decrease as the strength of the prime-probe association increases and as SOA increases. According to this analysis, it should be possible to indirectly assess the activation level of a probe as a function of SOA and the strength of the prime-probe association. Thus, the priming paradigm provides a basis for empirically discriminating between the Rate, Distance, and Threshold Models because the models make different predictions concerning how the level of activation of a pathway depends jointly upon its strength and upon processing time (see Figure 2). This argument will be developed more fully in the following sections.

Review of empirical findings from the priming paradigm. The effects of priming on probe task performance have been observed for several experimental tasks, including: lexical decision (e.g., Fischler, 1977a; James, 1975; Meyer & Schvaneveldt, 1975; Meyer, Schvaneveldt, & Ruddy, 1974; Shulman & Davison, 1977; Schuberth & Eimas, 1977; Tweedy, Lapinski & Schvaneveldt, 1977); naming (e.g. Jacobson, 1973; Meyer et al., 1974); phoneme monitoring (e.g., Foss, 1970; Foss, Cirilo, & Blank, 1979; Swinney & Hakes, 1976); production (e.g., Loftus, 1973; Loftus & Loftus, 1974); and sentence verification (e.g., Ashcraft, 1976; Collins & Quillian, 1970; Myers & Lorch, in press). Despite an extensive literature on semantic priming effects, however, there is not conclusive evidence to discriminate between the Rate, Distance, and Threshold Models. The available evidence is valuable for several reasons, though. First, it demonstrates the utility of the priming paradigm in assessing the activation process and it suggests procedural constraints on the investigation of that process. Second, it provides a further demonstration of the sufficiency of the general theoretical framework from which the three retrieval models are derived.

General findings. The results from many priming studies are consistent in indicating the existence of an automatic activation process. The characteristics of this process emerge from an examination of several important empirical findings. First, subjects are faster to perform a probe task if the prime is semantically related to the probe than if the prime and probe are unrelated or the prime is neutral (e.g., a row of asterisks). This result has been observed for several types of probe tasks, including: naming (Jacobson, 1973; Meyer et al., 1974); lexical decision (Meyer et al., 1974); production (Loftus, 1973; Loftus & Loftus, 1974); and sentence verification (Ashcraft, 1976; Myers & Lorch, in press). Second, performance on a probe task is facilitated if a semantically related prime precedes it even if the subject has no basis for expecting that the probe will be related to the prime (Fischler, 1977a; Tweedy et al., 1977). In fact, facilitation effects can result from a semantically related prime despite expectations that the probe will not be related to the prime (Neely, 1977). Neely's results are particularly relevant to the research to be reported in subsequent chapters because they provide some important parametric information regarding the time-course of the automatic activation process. In the lexical decision task employed by Neely, automatic priming effects developed within 400 milliseconds; evidence of a more deliberate processing strategy of switching attention from the prime word to some episodic associate of the prime was not present until somewhere between 550 and 850 milliseconds after presentation of the prime word.

Given that semantic priming effects occur and that they are at least partially attributable to automatic processes triggered by the prime, what are the attributes of this process? The Rate, Distance, and Threshold Models all predict that the magnitude of automatic facilitation effects should depend upon the strength of the prime-probe association. Considering studies in which the SOAs involved were within the range identified by Neely (1977) to implicate automatic activation processes (i.e., less than approximately 800 msec), there is some support for this prediction. Experiments by Kim (Note 4) and by Fischler and Goodman (1978) have demonstrated larger facilitation effects for strongly associated prime-probe word pairs than for weakly associated pairs in a lexical decision task. The effect of associative strength on the magnitude of the priming effect in the Fischler and Goodman study (Experiment 2) was present at an SOA of only 40 milliseconds. Other lexical decision experiments have failed to find strength effects on the magnitude of priming effects (Fischler, 1977b; Neely, 1977; Warren, 1977), but their null results may be due to a lack of statistical power: Both Neely and Warren used a median-split procedure to partition stimuli into high and low associative strength levels with the probable result that their strength manipulations were rather weak. Further, the magnitude of priming effects in the Warren naming experiment was only eight milliseconds for both high and low strength prime-probe pairs, indicating that his procedure was generally insensitive. (Warren instructed subjects to ignore the prime word, which may account for the small effects he observed.) Finally, although the result was not significant, priming effects in Fischler's lexical decision experiment were fifteen milliseconds larger for strongly associated prime-probe word pairs than for weakly associated pairs. To conclude, although the magnitude of the effects is not impressive, the evidence indicates that facilitation effects attributable to automatic processes triggered by the prime depend upon the strength of the association between the prime and probe. This conclusion is supported by the fact that several priming experiments employing SOAs between one and two seconds have demonstrated larger facilitation effects for strongly associated prime-probe pairs than for weakly associated pairs (Massaro, Jones, Lipscomb, & Scholz, 1978; Rosch, 1975; Sanford et al., 1977).

Finally, the Rate, Distance, and Threshold Models share the assumption that activation builds in an associative pathway over time to some limit (see Figure 2). The available evidence supports this claim. In the range of SOAs implicating automatic activation effects, facilitation effects have consistently been found to increase as SOA increases (Antos, 1979; Fischler & Goodman, 1978; Neely, 1976; Warren, 1977). The sole exception to this general finding comes from an experiment by Kim (Note 4), who found that facilitation effects had already asymptoted by 400 milliseconds, the shortest SOA included in his experiment.

To summarize, the review of findings from the priming paradigm has further demonstrated the theoretical sufficiency of the models under consideration. In addition, the review has established the utility of the paradigm for examining the activation process and has suggested some procedural constraints on the investigation of that process. Several results are consistent with the general spreading activation model common to the three models under consideration: (1) Semantic priming effects occur and are at least partially attributable to automatic consequences of attending to the prime. (2) Facilitation effects are often larger when the prime and probe are strongly associated than when they are weakly associated. (3) Automatic facilitation effects develop rapidly (at SOAs as short as 40 msec) and apparently build to an asymptote relatively quickly (perhaps within 400 msec). While these findings lend further support to the sufficiency of the Rate, Distance, and Threshold Models, they do little to discriminate the models. What is necessary to discriminate between the models is information concerning how the magnitude of semantic facilitation effects depends jointly upon the strength of the prime-probe association and upon the amount of time available for processing the prime (i.e., SOA).

Joint effects of strength and SOA on priming. There are few studies that provide information about the joint effects of SOA and the strength of the prime-probe association on automatic activation processes. Further, the evidence from the handful of relevant experiments is inadequate for the task of discriminating the Rate, Distance, and Threshold Models.

Fischler and Goodman (1978) examined the effects of SOA and the strength of the prime-probe association on latency to make a "word" decision in a lexical decision task. Prime-probe strength was assessed according to free association normative measures and the SOAs investigated were 40 and 550 milliseconds. At the 40 msec SOA, the priming effect was 62 msec for high association prime-probe pairs and 18 msec for low association items; at the 550 msec SOA, the priming effects for the high and low association items were 66 msec and 40 msec, respectively. Although it appears that priming effects have already asymptoted at the 40 msec SOA for the high association items while facilitation is increasing over SOA for low association items (and perhaps approaching a common asymptote with the high association items), no statistical test of this interaction is provided. Further, the trend is almost certainly not reliable because the data for the two SOAs comes from two different experiments with slightly different procedures and different subjects.

Using a lexical decision task, Kim (Note 4) examined prime-probe strength effects on priming at SOAs of 400, 600, and 800 msec. His results were that priming effects were constant across the three SOAs for high association items, while priming effects for low association items were the same at 400 and 600 msec, then decreased at the 800 msec SOA. Automatic activation effects had evidently asymptoted by the 400 msec SOA and conscious processes may have begun to affect performance by the 800 msec SOA, causing the decrease in priming for the low association items. Thus, Kim's experiment is inadequate to the task of discriminating the three retrieval models because his data do not address the issue of how activation builds up over time as a function of strength.

Finally, Warren (1977) used a naming task to examine prime-probe strength effects over four SOAs ranging from 75 to 225 msec. He found that priming facilitation occurred and increased over the range of SOAs from 75 to 150 msec, leveling off after that. There was no effect of prime-probe strength on the magnitude of the priming effects, however. For reasons noted earlier, Warren's procedures probably resulted in an insensitive test of strength effects on priming.

To summarize, the available data on the joint effects of prime-probe strength and SOA are scant and inconclusive. The necessary requirements for a definitive test of the Rate, Distance, and Threshold Models are lacking in the three studies considered above. The criteria for a sufficient test of the models are that the common predictions of the three models be verified: (1) An effect of the strength of the prime-probe association on the magnitude of the priming effects must be demonstrated. (2) Facilitation effects must be observed to increase over SOA. (3) Facilitation effects must asymptote within the range of SOAs examined. In other words, an adequate experimental test must map out two complete and empirically distinguishable priming functions -- one for each of two levels of prime-probe strength. When this goal is achieved, the task of discriminating the three retrieval models can be accomplished by determining how the two priming functions differ (see Figure 2). The experiments to be reported in the following chapters employ different experimental tasks with the common purpose of mapping out the activation function for strong and weak associations using either RT (Experiment 1) or priming (Experiments 2 and 3) as a measure of activation level.

General Summary

Much evidence has been reviewed which demonstrates the theoretical sufficiency of the Rate, Distance, and Threshold Models. All three models are able to account for data from a variety of paradigms demonstrating that the speed of retrieval of a memory trace increases as the strength of the trace increases. The ability to account for this data represents the minimal test of the sufficiency of the models as the models were all developed to account for the observation that retrieval is strength-ordered. Each of the models also provides an adequate exlanation of interference effects on retrieval latency; this ability is attributable in each case to the assumption that retrieval processing capacity is limited. Finally, because all three models adopt a spreading activation process as their search mechanism, all of the models are able to account for current findings in the priming literature.

It was proposed that the priming paradigm is ideally suited to the task of discriminating the Rate, Distance, and Threshold Models. Priming effects on probe task performance are attributable to the consequences of activating the memory structure corresponding to the prime during the interval between prime and probe presentation: The stronger the prime-probe association and the more time allowed for processing of the prime, the more highly activated the probe's memory structure should be at the time of probe presentation. On the assumption that RT is a monotonic decreasing function of the activation level of the probe's memory structure, then, the priming paradigm offers a direct approach to the goal of isolating and examining the activation process. If complete semantic priming functions can be established separately for strongly related and weakly related prime-probe pairs, a comparison of the functions should discriminate the three retrieval models by demonstrating the effects of strength on the rate of activation and on asymptotic activation (see Figure 2). Further, such data should represent an important contribution towards a descriptive model of the activation process (Bush & Mosteller, 1955; Estes, 1979). This task is taken up in the following chapter.

CHAPTER IV

EXPERIMENT 1: PRIMING A CATEGORIZATION DECISION

The first experiment uses a variant of the priming paradigm to examine the effect of strength on the time-course of the activation process. The experimental task is as follows. On each trial, the subject is presented the name of a semantic category followed by the name of a possible exemplar of the category. The subject's task is to decide whether the target exemplar is or is not an instance of the presented category. The subject's correct response times on positive trials are the data of first concern; RTs will be examined as a function of the strength of the category-exemplar relation and the interval between category and exemplar presentation, or SOA. A categorization task was chosen instead of a lexical decision task because it was hoped that priming effects would be larger in the former, "semantic" task. The SOAs chosen for inclusion in the experiment were selected to span the range of values representing automatic priming effects in Neely's (1977) study. Although Neely employed a lexical decision task, the priming stimulus in his experiment and in the present experiment is identical and thus the parametric values established by Neely seem relevant to the present experiment as well.

It is assumed that a subject makes a positive response in the categorization task based upon the retrieval of the actual category-exemplar relation; thus, RT will vary with the amount of time it takes to retrieve the category-exemplar association from memory (Lorch, Note 2). Specifically, it is assumed that when the name of the category is presented on a trial, the subject encodes the category and begins to activate associations of the category. When the target exemplar is presented, it is also encoded and a search is initiated from the concept-node corresponding to the exemplar. The simultaneous search for the category and exemplar nodes is assumed to be a parallel, intersecting activation process (Anderson, 1976; Collins & Loftus, 1975). When a pathway connecting the category and exemplar nodes is fully activated, it is selected and compared against the target "subset/superset" relation and a "yes" response is given if the retrieved relation matches the target relation. Thus, RT to make a positive response is assumed to vary directly with the time it takes to activate and select the single "subset/superset" pathway connecting the category and exemplar nodes in memory.

What are the predictions of the three retrieval models concerning performance on positive trials? Note that the category name functions both as a prime and as part of the probe task in the experimental paradigm. As a consequence, increasing the interval between presentation of the category and exemplar words will result in a reduction of RTs relative to the simultaneous presentation condition (i.e., SOA = 0 msec). This is because longer SOAs will give the subject a greater headstart on processing the category word (e.g., encoding) and on activating associations of the category (including any connections to the upcoming exemplar). At short SOAs, subjects will not have sufficient time to activate associations and RT will thus be faster to strong category-exemplar pairs than to weak pairs according to all three models. This prediction follows because all three models hypothesize that strong pathways are retrieved faster than weak paths. Thus, all three models predict that RT will be faster to strong than to weak associates, on the average. At sufficiently long SOAs, subjects should be able to encode the category word and fully activate all available associates of the category before the exemplar word is even presented. As a consequence, subjects need only select the appropriate pathway in memory and evaluate it against the target relation when the exemplar word is presented. Thus, all of the models predict that RT will decrease to some asymptote as SOA increases. The contrasting predictions of the models are of greater interest.

A summary of the predictions of the Rate, Distance, and Threshold Models is presented in Figure 4. First, both the Rate and the Distance Model hypothesize that strength directly determines the duration of the activation process, with strong pathways being activated sooner than weak pathways. Thus, both models predict that RTs will asymptote at a shorter SOA in the case of strongly associated category-exemplar pairs than in the case of weakly associated pairs. Further, both models predict that the strong and weak association functions will asymptote at the same RT. This prediction follows because the source of RT differences -- differences in the duration of the activation process -- will be eliminated as a component of RT at sufficiently long SOAs. In contrast, the Threshold Model predicts that although RT will decrease

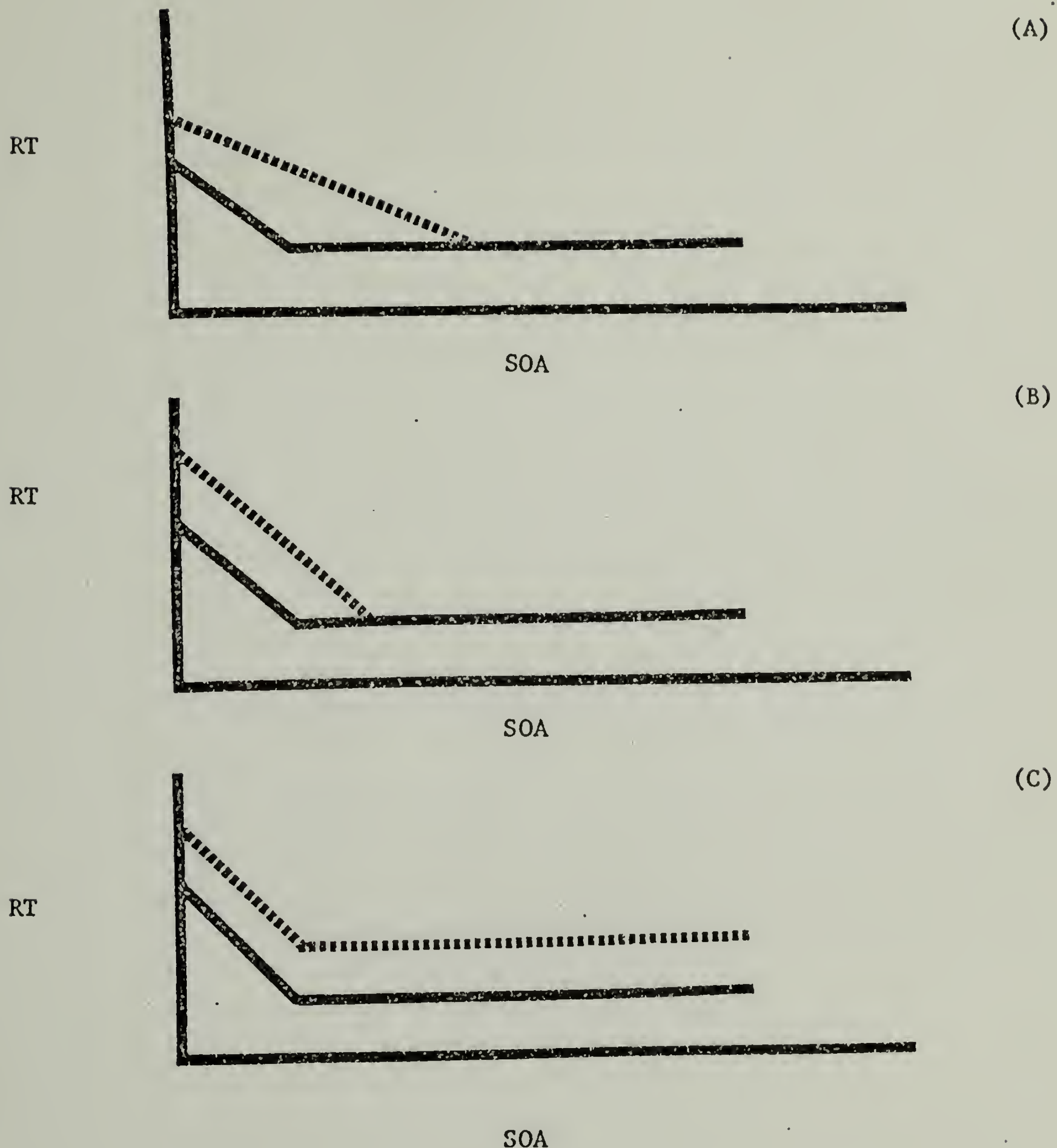

Figure 4. Predicted effects on reaction times of SOA and associative strength. Predictions are presented separately for the Rate Model (A), Distance Model (B), and Threshold Model (C). Solid lines designate a strong association and dashed lines denote a weak association.

over SOA, the magnitude of the strength effect will not vary over SOA. This prediction follows from the fact that the model attributes strength effects to the selection process rather than to differences in the duration of the activation process: RT will decrease as SOA increase because of the headstart conferred on encoding and activation, but the process of selecting the actual category-exemplar relation for evaluation cannot begin until the exemplar word is presented. Since strength effects are attributed to the selection process rather than to the activation process, the effect of strength will not depend upon SOA.

A final set of contrasting predictions concerns the rate of decrease in reaction time as a function of strength. Under the most reasonable set of assumptions for processing in the categorization task, the Rate Model stands alone in predicting that as SOA increases, RT will decrease at a faster rate preasymptotically for strong associates than for weak associates. Let us consider this prediction in some detail. The Rate Model is represented graphically in Figure 5. In general, the activation level at time _t_ (A_t) equals the rate of activation (r) times the processing time (t) when the activation function is below asymptote, while the activation level is maximal elsewhere (A_{max}):

$$(1) \qquad \begin{array}{ll} A_t = rt & t > t_{critical} \\ A_t = A_{max} & t \leq t_{critical}, \text{ where } t_{critical} = A_{max}/r \end{array}$$

For the categorization task, the rate of activation depends upon whether the association is strong or weak and whether the search is from just

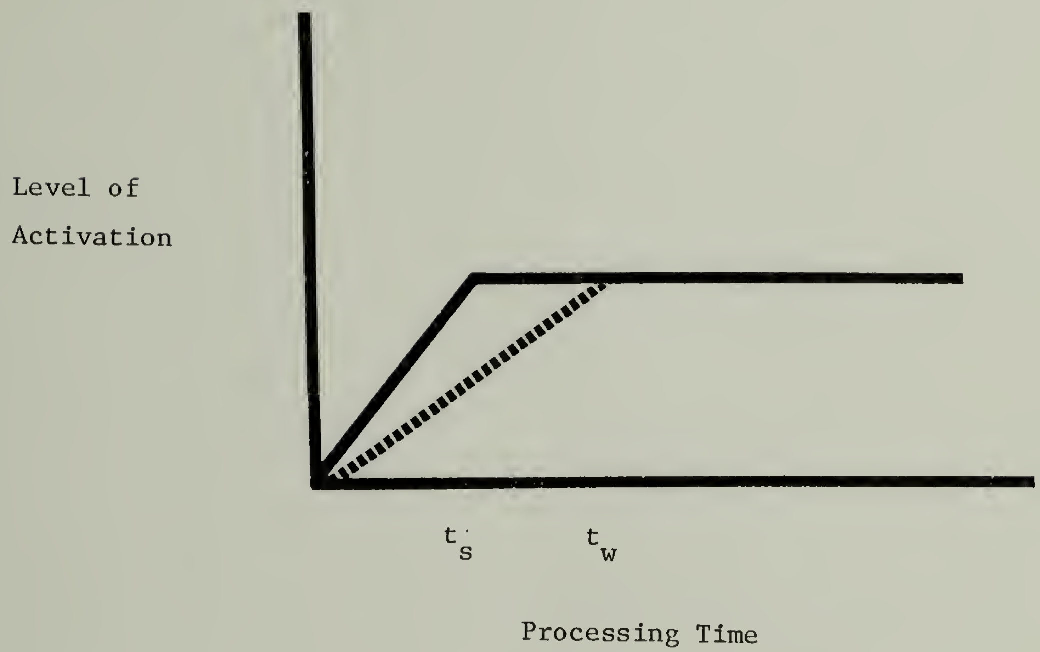

Figure 5. The rate of change in level of activation as a function of strength according to the Rate Model. The solid line designates a strong association and the dashed line designates a weak association.

the category node or from both the category and exemplar nodes. The rate of activation is assumed to be faster for strong than for weak associates, $r_s > r_w$, and activation is faster when search proceeds from two nodes than when it proceeds from just one, $r_s' > r_s$ and $r_w' > r_w$. The time it takes to respond on a trial in the categorization experiment may be represented as consisting of the time it takes to complete all processes excluding search (W) plus the time it takes to complete the activation process after the exemplar is presented, or $(A_{max} - A_t)/r'$. Putting this together, we obtain the following relationship between RTs to weak versus strong associates when both activation functions are below asymptote (i.e., $t < t_s$):

$$(2) \quad RT_w - RT_s = [W + (A_{max} - A_{t_w})/r_w'] - [W + (A_{max} - A_{t_s})/r_s'] \\ = A_{max}\left(\frac{1}{r_w'} - \frac{1}{r_s'}\right) - t\left(\frac{1}{r_w'} - \frac{1}{r_s'}\right)$$

According to this result, when $t = 0$, $RT_w - RT_s$ will be positive because $r_w' < r_s'$ and $1/r_w'$ is consequently greater than $1/r_s'$. In other words, there will be an effect of strength on RT in the simultaneous presentation condition. The concern is with how the magnitude of the strength effect will vary as t increases beyond 0 but below t_s; this information is provided by the right-hand side of Equation 2. The conclusion depends upon whether the increase in the activation rate resulting from presentation of the exemplar word is greater for the weak or for the strong associates or is the same for both associates. If the proportional increase in the search rate is the same, then r_w/r_w' will equal r_s/r_s', their difference will be zero and the strength effect will be constant over SOA. If the rate of activation increases propotionately more for strong associates than for weak, then r_w/r_w' will be greater than r_s/r_s', their difference will be positive and the strength effect will decrease over SOA. Finally, if the activation rate increases proportionately more for weak than for strong associates, then r_w/r_w' will be less than r_s/r_s', their difference will be negative and the strength effect will increase over SOA. This last assumption seems the most reasonable because it seems most plausible that the search process will benefit more by presentation of the exemplar word in the case of weak associates than in the case of strong associates. This is the prediction depicted in Figure 4.

In contrast to the Rate Model's prediction that the strength effect will vary over SOA, the Distance and Threshold Models both predict that the strength effect will be constant over SOA (at least pre-asymptotically). This can be seen in the context of the derivations presented above for the Rate Model. The Distance and Threshold Models hypothesize that the activation rate is the same for strong and weak associates, or that $r_w = r_s$ and $r_w' = r_s'$. Thus, the increase in the search rate as a result of presenting the exemplar word is the same for strong and weak associates and the strength effect is predicted to be constant over SOAs until RT asymptotes for the strong associate.

To summarize, all three models predict that: (1) on the average, strong associates will be responded to faster than weak associates on positive trials; and (2) RT will decrease to some asymptote as SOA increases. The contrasting predictions of the models concern: (1) How the magnitude of the strength effect will depend upon SOA; (2) Whether the RT functions for the strong and weak associates asymptote at the same or different SOAs; and (3) Whether the two RT functions approach their asymptotes at the same or different rates.

Method

Materials. Four types of category exemplar pairs were generated for use in the experiment: strongly associated true items (e.g., Animal-Cat); weakly associated true tiems (e.g., Animal-Bull); strongly associated false items (e.g, Animal-Cracker); and weakly associated false items (e.g., Animal-Boston). A total of 49 different categories were chosen from the Battig and Montague (1969) and Shapiro and Palermo (1970) norms to be used as the category words in the experiment. All categories could be given one-word labels. One or two pairs of exemplars were then chosen from each category and the exemplars were each paired with the category name to form true category-exemplar items. The pairs of exemplars differed in dominance, or the frequency with which each was produced as an instance of its semantic category in the association norms. Since dominance is a measure ofthe availability of a particular exemplar of a stimulus category and since dominance is correlated with several other possible indicators of strength (e.g., typicality ratings), it was adopted as the operational definition of strength in all three experiments to be reported.

A complete list of the critical items for the experiment is presented in Table 5 in Appendix A. Before describing the procedure for constructing the false items, a couple of observations are in order concerning the characteristics of the true items. First, the paramount consideration in selecting the items was that the manipulation of dominance be an extreme one. This goal was accomplished: the mean percentage of subjects producing the high dominant exemplars was 83.5 (SD = 11.27; Range = 41%-100%); the corresponding percentage for the low dominant exemplars was 8.6 (SD = 4.28; Range = 2%-22%). The extreme manipulation of dominance was bought at the cost of a confounding with the frequency of English language usage (Kucera & Francis, 1967) of the exemplar word: High dominant exemplars are more frequent in the English language than low dominant exemplars (M = 78.7, SD = 110.7 for high dominant exemplars; M = 28.3, SD = 44.4 for low dominant exemplars). This confounding was permitted because controlling word frequency would have required a less extreme dominance manipulation. Further, dominance effects have been demonstrated in several similar experiments in which word frequency has been controlled (Holyoak & Glass, 1975; Lorch, Note 2; Myers & Lorch, in press), thus it seems safe to attribute the expected dominance effects to the associative strength manipulation. Finally, note that the category words for the high and low dominant items are exactly the same. This procedure was followed to insure that the distribution of associates of the prime word was the same for the high and low dominant items because there is abundant evidence that the distribution of associates of a concept will influence the retrieval of any given associate (see Chapter III).

Next, consider the procedure for constructing false items for the experiment. Two nonexemplars were generated for each category that was used in constructing a true item; one nonexemplar was associated with the category word (e.g., Animal-Cracker) and one was unrelated to the category (e.g., Animal-Boston). Associated nonexemplars were generated both intuitively and with the aid of association norms (Ashcraft, 1978b; Jenkins, 1970; Keppel & Strand, 1970); unrelated nonexemplars were primarily low dominant exemplars selected from categories in the Battig and Montague (1969) and Shapiro and Palermo (1970) norms. The unrelated nonexemplars were paired with categories by a random assignment procedure. A total of 77 associated and 77 unrelated category-exemplar pairs were generated for use as critical items in the experiment; these stimuli are presented in Table 5 in Appendix A. The mean word frequency for the associated nonexemplars was 84.2 (SD = 116.4), while the mean word frequency for the unrelated nonexemplars was 72.4 (SD = 83.9).

In addition to the critical items, 216 filler items were constructed for use as practice and warm-up items; there were 54 items representing each of the four item-types.

After all of the items to be used in the experiment had been constructed, they were assigned to blocks. There were 8 blocks of 52 items each. In each block, there were: 11 high dominant true items; 11 low dominant true items; 11 associated false items; 11 unrelated false items; 2 high dominant true filler items; 2 low dominant true fillers; 2 associated false fillers; and 2 unrelated false fillers. The first block of items consisted of practice items and the remaining 7 blocks consisted of 8 fillers and 44 critical items each. The filler items were always the first 8 trials of each block; their purpose was to serve as warm-up trials. The assignment of critical items to blocks was done at random (within the above constraints) and independently for each subject in the experiment. Further, each of the 7 test blocks was assigned to a different SOA condition. Thus, the assignment of critical items to a given SOA x dominance x truth-value combination was different for each subject.

<ins>Design</ins>. The design of the experiment was essentially: 2 (high or low dominance) x 2 (true or false item) x 7 (SOA = 0, 100, 200, 300, 400, 500 or 600 msec) x 49 (subjects). All variables were manipulated within subjects and the subjects factor was a random effects variable. Finally, the order of presentation of the 7 SOA conditions was determined separately for each subject using a Latin-square procedure: Seven different Latin squares were employed to assign a unique sequence of SOA conditions to each of the 49 subjects such that each SOA value occurred 7 times in each ordinal position in the sequence across subjects.

<ins>Procedure</ins>. Subjects were tested individually in an experimental session lasting approximately 45 minutes. Subjects were seated in front of a video display screen with each hand resting at a response lever. The sequence of events on each trial was the same: First, three "X's" appeared on the display screen to signal the start of the trial and to indicate where the category word would appear. Next, after a delay of

750 milliseconds, the "X's" were erased and replaced with the name of a category. Third, the target exemplar was presented two lines below the category word after a variable delay ranging from 0 to 600 milliseconds, depending upon the SOA condition. Subjects were instructed to read the category word silently when it appeared, then decide whether the target exemplar was a member of the category or not. They were instructed to pull the right-hand response lever to respond positively and the left-hand lever to indicate that the target word was not an exemplar of the category. If the subject's response was correct, the category-exemplar pair on the screen was erased immediately and a new trial began after a delay of three seconds. If the subject made an error or if four seconds elapsed without a response after the target exemplar was presented, then the category-exemplar pair was replaced by the word "ERROR" and the intertrial interval was not initiated until the subject indicated that she was ready by pulling either response lever. Subjects were instructed to respond quickly but accurately. A copy of the instructions is presented in Appendix B.

The sequence of trials within each block was randomized independently for each subject with the constraint that the first eight trials of each block consist of the filler items. The assignment of stimuli to blocks, the sequencing of trials within blocks, the presentation of stimuli and the timing of trials, and the collection of trial data were all controlled by a PDP-8E computer. Finally, it should be noted that the SOA value assigned to the practice block was the same as the SOA assigned to the first test block for each subject.

Subjects. A total of 53 subjects (35 women) participated in the experiment. All of the subjects were undergradaute students in psychology courses at the University of Massachusetts and they received experimental credit for their participation. Four subjects were replaced: one subject was not a native American; one subject was ill and on medication, but did not inform the experimenter until the completion of the experiment; and two subjects failed to follow instructions.

Results and Discussion

Data analysis procedures. Each subject's mean RT for correct responses was calculated for each dominance x truth-value x SOA condition in the experiment and these data were submitted to several fixed effects, repeated-measures ANOVAs. Each datapoint represented a mean RT over a maximum of the eleven items in a given experimental condition. Although the data were averaged over stimuli, the results of the statistical tests of most of the treatment effects may be generalized to the population of items from which the stimuli were sampled (Clark, 1973). This is because the items representing a particular treatment condition were unique for each subject. The only exceptions are the tests of the main effects of dominance and of truth-value, and the interaction of dominance and truth-value. No tests were conducted of the generalizability of these effects over items, however, because these effects have been replicated by many investigators using different samples of items (Lorch, Note 2; Rips, Shoben, & Smith, 1973; Schaeffer & Wallace, 1969;

1970; Wilkins, 1971).

Separate analyses were performed on the true and false data. Trend analyses were performed on the RT data and polynomial functions were estimated for both the true and false data. In addition, several subsidiary analyses were performed on the true RT data. The total number of errors made in each condition was also calculated for each subject, then analyzed. Separate trend analyses were performed on the data for the true and false items. Unless noted otherwise, all reported results were significant beyond $p = .005$.

Findings for true responses. The results for the experiment are presented in Table 1. The data of primary concern are the RT data for true responses. In order to facilitate the process of evaluating the three models against these data, a graph of the results is presented in Figure 6. The first thing to note about these data is that the experiment succeeded in mapping out the time-course of the activation process as evidenced by the fact that both the high dominant RT function and the low dominant RT function decrease monotonically to their respective asymptotes. Further, there is evidently a large effect of dominance on RT. Thus, the data meet the criteria for a sufficient test of the Rate, Distance, and Threshold Models.

Given that the data map out the time-course of the activation process, how do the three models fare in their predictions concerning how activation depends upon strength? Comparing the results presented in Figure 6 with the theoretical predictions depicted in Figure 4, it is

TABLE 1

REACTION TIMES (IN MSEC) AND PERCENTAGE ERRORS (IN PARENTHESES) AS A FUNCTION OF EXPERIMENTAL CONDITION IN EXPERIMENT 1

	True Responses SOA							
Dominance	0	100	200	300	400	500	600	Mean
High	999 (0.68)	876 (1.70)	836 (1.36)	753 (1.70)	752 (1.02)	738 (1.19)	743 (1.02)	814 (1.24)
Low	1183 (8.50)	1040 (7.48)	1010 (9.18)	946 (6.80)	893 (8.33)	922 (9.18)	961 (8.33)	994 (8.26)
Difference	184 (7.82)	164 (5.78)	174 (7.82)	193 (5.10)	141 (7.31)	184 (7.99)	218 (7.31)	180 (7.02)

	False Responses SOA							
Dominance	0	100	200	300	400	500	600	Mean
High	1254 (8.84)	1123 (7.14)	1060 (7.65)	965 (6.63)	940 (6.29)	947 (5.78)	978 (5.44)	1038 (6.82)
Low	1141 (1.53)	964 (0.51)	918 (0.68)	839 (0.85)	798 (0.68)	795 (0.51)	804 (1.36)	894 (0.87)
Difference	113 (7.31)	159 (6.63)	142 (6.97)	126 (5.78)	142 (5.61)	152 (5.27)	174 (4.08)	144 (5.95)

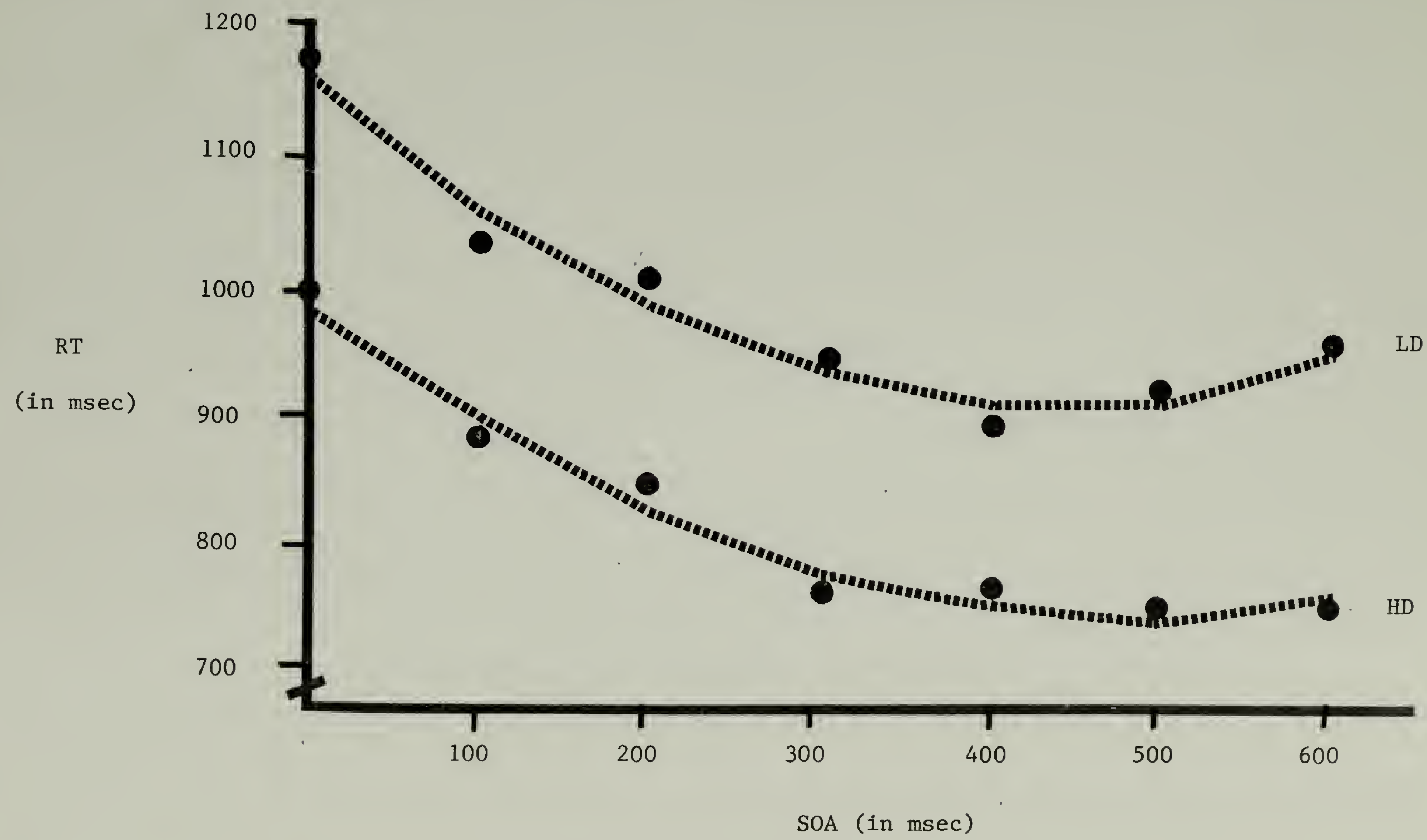

Figure 6. Reaction times for true responses plotted as a function of SOA and the dominance of the exemplar in Experiment 1. HD = High dominance; LD = Low dominance. Data are plotted as points and the best-fitting polynomial functions are plotted as dotted curves.

evident that the Threshold Model provides the best account of the findings: As the model predicted, there appears to be a constant effect of dominance over SOAs. This conclusion is supported by a trend analysis on the data. There was a large dominance effect; subjects were 180 msec faster to respond "true" when the exemplar was a high dominant member of the category than when the exemplar was a low dominant member, $F(1,48) = 272.93$. Further, RT decreased substantially as SOA increased until it reached a minimum at the longest SOA values; the linear component of the SOA effect was significant, $F(1,48) = 119.46$, as was the quadratic component, $F(1,48) = 98.79$. No other effect was reliable and, in particular, the dominance x SOA(lin) interaction did not approach significance, $F < 1$. The complete results of the trend analysis are presented in Table 8 of Appendix C. The best-fitting polynominal function was calculated for each dominance condition (Myers, 1979) and they are plotted as dotted lines in Figure 6. The estimates of the beta-weights for the polynomial functions are: for the high dominant responses, B_1 (linear) = -40.29, B_2 (quadratic) = 11.12; for the low dominant responses, B_1 = -36.39, B_2 = 14.61. Thus, the difference in the slopes of the best-fitting lines to the high and low dominant RTs is only 3.9 msec; the statistical power of the test of the difference in the slopes was sufficient that an observed difference of only 10 msec would have resulted in a significant dominance x SOA(lin) interaction.

In order to more closely evaluate the fit of the Threshold Model to the data, several additional analyses were conducted to test the specific predictions of the model. First, the model hypothesizes that the rate of activation of an associative pathway does not depend upon the strength of the association. The resulting prediction that RT should decrease over SOA at the same rate for strong and weak associates was further tested by analyzing the data for just those SOAs over which RT was decreasing for both the high and low dominant items (i.e., for SOAs 0 through 300 msec). The results of this trend analysis were completely consistent with those of the overall analysis (see Table 9 of Appendix C). The main effect of dominance was again significant, $F(1,48) = 209.77$. In addition, the linear component of the SOA effect was significant, $F(1,48) = 142.34$, while the curvilinear component of the SOA effect was marginally significant, $F(2,96) = 3.65$, $p = .05$. Finally, the dominance x SOA(lin) interaction was not significant, $F < 1$. The estimates of the beta-weights are: for high dominant items, $B_1 = -74.10$, $B_2 = 19.75$; for low dominant items, $B_1 = -77.80$, $B_2 = 10.00$. Again, the statistical power was considerable -- if the difference in the slopes had been only 13 msec, the result would have been significant.

The Threshold Model predicts that the high and low dominance RT functions should be parallel not only over the decreasing portions of the functions, but also over the asymptotic portions of the functions. This prediction follows from the fact that the model attributes the dominance effect to a stage of processing subsequent to the activation process, while the effect of SOA is attributed to the activation process. Two sets of F-tests were conducted to further scrutinize the parallelism of the two RT functions. The first set of tests calculated the dominance x SOA interaction for all possible pairs of SOAs; the results of these tests are presented in Table 10 of Appendix C. Two results are of interest. First, a marginally significant interaction for the comparison of the dominance effects at SOAs of 300 and 400 msec suggests that the low dominant function may be asymptoting later than the high dominant function, $F(1,48) = 4.00$, $p = .051$. This suggestion contradicts the Threshold Model's claim that the duration of the activation process does not depend upon strength. Second, the increase in RT between the 400 and 600 msec SOAs for the low dominant function but not for the high dominant function resulted in the only other significant dominance x SOA interaction, $F(1,48) = 5.36$, $p = .025$. A second set of F-tests was done to assess the effects of SOA for all pairwise combinations of SOAs; separate analyses were done on the high and low dominant items. The results of these analyses are reported in Table 11 in Appendix C. Of interest in these analyses is the corroborating evidence that the high and low dominant RT functions asymptote at different points in time and that the increase in RT at the longest SOA values is reliable for the low dominant items: The decrease in RT from SOA = 300 msec to SOA = 400 msec was a marginally significant 52.5 msec for the low dominant function, $F(1,48) = 4.26$, $p = .045$; the effect was only 1.2 msec for the high dominant function, $F < 1$. The upswing in RT from SOA = 400 msec to SOA = 600 msec was also marginally significant for the low dominant items, $F(1,48) = 4.50$, $p = .039$. Thus, the additional analyses demonstrated two potential deviations from the parallelism predicted by the Threshold Model.

A potentially serious challenge to the Threshold Model is posed by the finding that RT apparently decreased for longer in the case of the low dominant items than in the case of the high dominant items. The model claims that the duration of the activation process does not depend upon strength, but this result is a suggestion to the contrary. There is some reason to doubt the validity of this result both because: (1) there were no controls for family-wise error rate across either set of tests demonstrating this effect (Myers, 1979); and (2) the deviation was not large enough to affect the test for parallelism across all SOAs in the overall trend analysis. Regardless of whether the effect is to be believed, perhaps the important observation is that even if the result does indicate that strength has an effect on the duration of the activation process, the effect of strength is small relative to the strength effect on the selection process (as indicated by the substantial effect of dominance even after both RT functions have reached their minima).

The second finding that RT increased over the two longest SOAs for the low dominant items is of little theoretical consequence in the present context. The result may indicate that conscious processes were playing a role in priming at the longest SOAs (Neely, 1977). According to this suggestion, the upturn in the low dominant RT function represents interference effects due to conscious processes. In any event, the important observation is that the concern is with the nature of the effect of strength on the activation process and the fact that both RT functions reached their minima by the 400 msec SOA indicates that activation had reached its maximum level by that point.

In addition to the analyses of the reaction time data reported above, a trend analysis was performed on the error data for true responses (see Table 12 in Appendix C). As can be seen in Table 1, the overall error rate was only 4.75 percent. The only reliable result was that subjects made more errors on low dominant items (8.26%) than on high dominant items (1.24%), $F(1,48) = 208.46$. This result replicates the findings of several previous investigations (Lorch, Note 2; Myers & Lorch, in press; Rips et al., 1973). No other effects were significant.

Finally, some discussion of the implications of the confounding of dominance and word frequency is in order. Based on results from lexical decision studies (e.g., Becker, 1979; Scarborough, Cortese, & Scarborough, 1977), it might be expected that high frequency words would be encoded more rapidly than low frequency words in the present categorization experiment. Such an effect would partially account for the main effects of dominance in the RT and error data. It is doubtful that the effects of dominance observed in this experiment are entirely attributable to the confounding with frequency because dominance effects have been observed in similar experiments when frequency has been controlled (Lorch, Note 2; Myers & Lorch, in press). Further, the effects of dominance would appear to be much larger than any that would be expected if frequency was the primary determinant of performance in Experiment 1. Finally, the theoretically important observation concerned the joint effects of strength and SOA; there was no basis for suspecting that frequency would interact with SOA and, of course, there was no evidence of such an effect. Thus, the confounding of frequency and dominance does not alter the interpretation of results presented above.[1]

To summarize, while there are some doubts about the relative points of asymptote of the high versus low dominant RT functions, the overall fit of the Threshold Model to the true response data is remarkably good. The Rate and Distance Models do inadequate jobs of accounting for these data, as can be quickly ascertained by comparing the theoretical predictions of the models summarized in Figure 4 with the actual results graphed in Figure 6. The data thus suggest that strength effects are not attributable to effects on the duration of the activation process; rather, the activation process occurs equally rapidly for all associates regardless of strength. The effect of strength appears to be localized in a stage of processing occurring subsequent to search. Further support for this conclusion is presented in the data for false responses.

<u>Findings for false responses</u>. The data for false responses are not of primary concern because no adequate processing model has been developed for false responses. Nevertheless, the false response data are striking for their similarity with the true response data and thus deserve consideration.

The false response data are presented in Table 1 and are graphed in Figure 7. As can be seen in Figure 7, RT decreased at the same rate

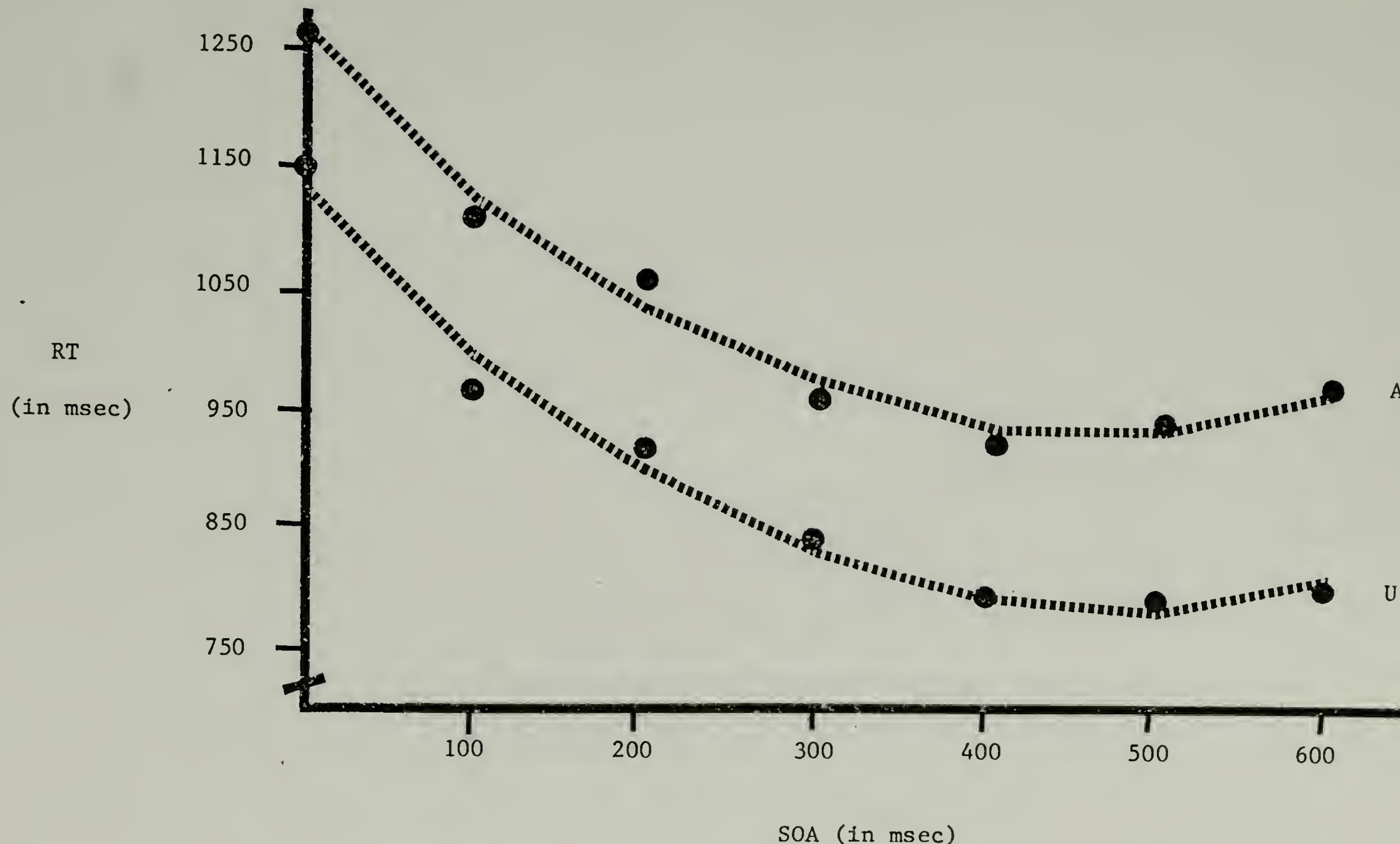

Figure 7. Reaction times for false responses plotted as a function of SOA and strength of association for Experiment 1. A = associated exemplar; U = unassociated exemplar. Data are plotted as points; best-fitting polynomial functions are plotted as dotted curves.

to different asymptotes for the associated and unrelated false items. A trend analysis on the RT data confirms the parallelism of the functions (see Table 13 in Appendix C). First, subjects were 144 msec faster to respond "false" when the category and nonexemplar were unrelated than when they were associated, $F(1,48) = 141.32$. Note that the effect of strength is the reverse of the strength effect found for true responses, a result that has been observed repeatedly in similar experimental situations (Lorch, Note 2; Rips et al., 1973; Schaeffer & Wallace, 1969; 1970). Second, RT decreased to an asymptotic value as SOA increased; both the linear component of the SOA effect, $F(1,48) = 224.68$, and the quadratic component of the SOA effect were significant, $F(1,48) = 69.81$. Finally, no other effect was reliable, although the "dominance" x SOA(lin) interaction was in the direction of the strength effect increasing as SOA increased, $F(1,48) = 2.38$, $p = .129$. As in the case of the true response data, the best-fitting polynomial functions were estimated for the false response data and are plotted as dotted curves in Figure 7. The estimates of the beta-weights are: for associated items, $B_1 = -46.43$, $B_2 = 15.48$; for unrelated items, $B_1 = -52.46$, $B_2 = 14.54$. It might be noted that the slope parameters estimated for the false response data are larger in absolute magnitude than those estimated for the true response data. This difference was reliable, indicating that RT decreased more over SOA for false items than for true items, [$F(1,48) = 12.88$, for the truth-value x SOA(lin) interaction].

In addition to the RT results reported above, there were some reliable effects of SOA and of "dominance" on the number of errors subjects made (see Table 14 in Appendix C). First, subjects made more errors on associated items (6.82%) than on unassociated items (0.87%), $F(1,48) = 130.67$. This finding replicates the observations of several previous investigations (Lorch, Note 2; Rips et al., 1973; Schaeffer & Wallace, 1969; 1970). Second, it can be seen in Table 1 that errors on associated items decreased as SOA increased, while there was no consistent effect of SOA on errors to unrelated items; this conclusion is indicated by a significant "dominance" x SOA(lin) interaction, $F(1,48) = 6.62$, $p = .013$. Finally, there was some indication from a Latin square ANOVA that errors on false items decreased with practice, $F(6,564) = 3.65$, $p = .05$; subjects made more errors in the first three blocks of trials (4.68%) than in the final four blocks (3.23%). A similar analysis on the true response data demonstrated an unreliable trend in the same direction, $F < 1$; subjects made more errors in the initial three blocks (4.40%) than in the final four blocks (3.45%).

Integration of findings. Although the Threshold Model can account for the finding that SOA and dominance have independent effects on RT, the model is insufficiently specified to offer an account of the pattern of results as a function of dominance and truth-value. A processing model which does offer an adequate explanation of the dominance x truth-value interactions proposes that responses in the categorization task represent a mixture of fast, nonanalytical decisions and slower, more analytical judgments of the category-exemplar relation (Gellatly &

Gregg, 1977; McCloskey & Glucksberg, 1979; Meyer, 1970; Schaeffer & Wallace, 1969; 1970; Smith, Rips, & Shoben, 1974; Smith, Shoben, & Rips, 1974). Specifically, the model proposes that in the initial stage of processing the associative pathway between the category and exemplar is activated to a level that is strength-dependent, but at a speed which is independent of strength. When the pathway is fully activated, it is selected and evaluated at a speed which is dependent upon its activation level: If the activation level is very high or very low, the item is classified as true or false, respectively, with little further evaluation; if the activation level is intermediate, the pathway label is more carefully evaluated to determine whether it matches or contradicts the target "subset/superset" relation. Such a decision strategy is made possible by the confounding of "dominance" and truth-value present in the experiment (cf., Smith et al., 1974a; 1974b).

How does the proposed processing model account for the findings of Experiment 1? As before, the decrease in RT as SOA increases is attributed to the headstart conferred on encoding and activation, while the independent effects of SOA and dominance are explained by the model's claim that the variables influence different stages of processing. The relatively fast responses to high dominant true items and to unrelated false items are attributed to the hypothesis that a high proportion of these items will receive only a cursory evalution during the decision stage (Smith et al., 1974a; 1974b). The high error rates on low dominant true items and on associated false items are attributed to the high probability that subjects will misclassify these items when they use a level-of-activation judgment as the basis for their decision-making (Smith et al., 1974a; 1974b).

In addition to the central findings considered above, the model offers plausible accounts of some secondary effects of practice and of SOA on errors to false items. These results appear attributable to systematic shifts in subjects' criteria for a negative response. It seems reasonable to assume that subjects' criteria for a negative decision should be less stable than their positive decision criteria: The true items represent well known facts and thus the basis for responding to these items is clear; the false items consist of word pairs representing a variety of conceptual relations and thus subjects must learn what sorts of false items to expect and adjust their decision criteria accordingly. Consistent with this view is the fact that all of the secondary results represent effects on false responses that did not occur for true responses. First, the claim that subjects must "learn what a false item looks like" is supported by the tendency for errors on false items to decrease with practice. Second, the finding that errors on associated false items decreased as SOA increased may also represent a criterion shift. To the extent that subjects felt pressured to respond quickly in the task, they would be likely to cut short their processing on time-consuming items, i.e., associated false items presented at short SOAs. As SOA increased and RTs to all items became relatively fast, subjects could afford to more fully evaluate any given item with the result that accuracy improved most for the most difficult items. Finally, the finding that RT decreased more over SOA for false items than for true items is generally consistent with the suggestion that subjects were systematically shifting their criteria for a negative decision as a function of SOA.

Summary. Experiment 1 discriminates rather conclusively between the Rate, Distance, and Threshold Models. Contrary to the common prediction of the Rate and Distance Models that RT should decrease over SOA to a common asymptote for strongly and weakly associated items, the effect of strength was constant across SOAs. This result contradicts the claim that strength determines the duration of the activation process. The result is consistent with the Threshold Model's claim that strength determines the level of activation of an associative pathway, which, in turn, influences subsequent processing of the association. A model of the selection process was proposed which hypothesized that strength determines the extent to which an association will be evaluated in the categorization task (Meyer, 1970; Smith et al., 1974a; 1974b). The model provided an adequate account of the effects of dominance and truth-value on both RTs and errors, as well as suggesting explanations for some secondary effects of practice and of SOA on errors to false items. Thus, the Threshold Model provides a remarkably good fit to the data of Experiment 1; Experiment 2 tests the generality of the model by examining the effects of SOA and strength in a different experimental task.

CHAPTER V

EXPERIMENT 2: PRIMING A NAMING RESPONSE

The second experiment utilizes a simple probe task to examine the effect of strength on the time-course of the activation process. On each trial in the task, the subject is presented either the name of a semantic category or the word "blank." After an interval ranging from 150 to 600 msec, the name of an exemplar is presented and the subject's task is simply to say the exemplar word aloud as quickly as possible. When the prime consists of a category name, the probe word is always an exemplar of the category. The dependent variable of interest is the priming effect, or the difference between correct RT on a category prime trial and correct RT on its corresponding neutral prime trial. Priming effects will be examined as a function of the strength of the category-exemplar association and SOA.

The process model for the experimental task is as follows. It is assumed that when a category prime is presented, the subject encodes the category name and begins to activate associates of the prime including the to-be-presented exemplar; when a neutral prime is presented, of course, no information is provided about the upcoming probe. Contrary to the case for the categorization task, the prime word and its association to the probe are logically irrelevant to the requirements of the probe task. Nevertheless, a category word may activate the memory structure corresponding to the upcoming probe and thus facilitate processing of the probe. It is assumed, however, that the maximal level of activation of the probe's memory structure by the category prime is below that level of activation necessary for performance of the probe task. When the exemplar word appears, word recognition processes take over the job of probe processing: The exemplar word is encoded and its articulatory representation is retrieved and executed.

What are the predictions of the Rate, Distance, and Threshold Models concerning the effects of SOA and the strength of the prime-probe association on the magnitude of priming effects in Experiment 2? Since it is assumed that priming effects are a direct measure of the activation level of the probe resulting from processing the prime, the predictions of the three models may be readily derived from Figure 2; these predictions are presented in Figure 8. All of the models predict that priming effects will increase to some asymptote as SOA increases and that priming facilitation will be greater, on the average, when the prime and probe are strongly associated than when they are weakly associated. The contrasting predictions of the models are analogous to those derived for Experiment 1.

First, the Rate and Distance Models both predict that priming facilitation will initially be greater and will asymptote sooner for strong than for weak associations, but that facilitation effects will eventually asymptote at the same level for strong and weak associates. These predictions follow from the common hypothesis of the two models that strength determines the duration of the activation process and from the assumption that a single associative connection -- the

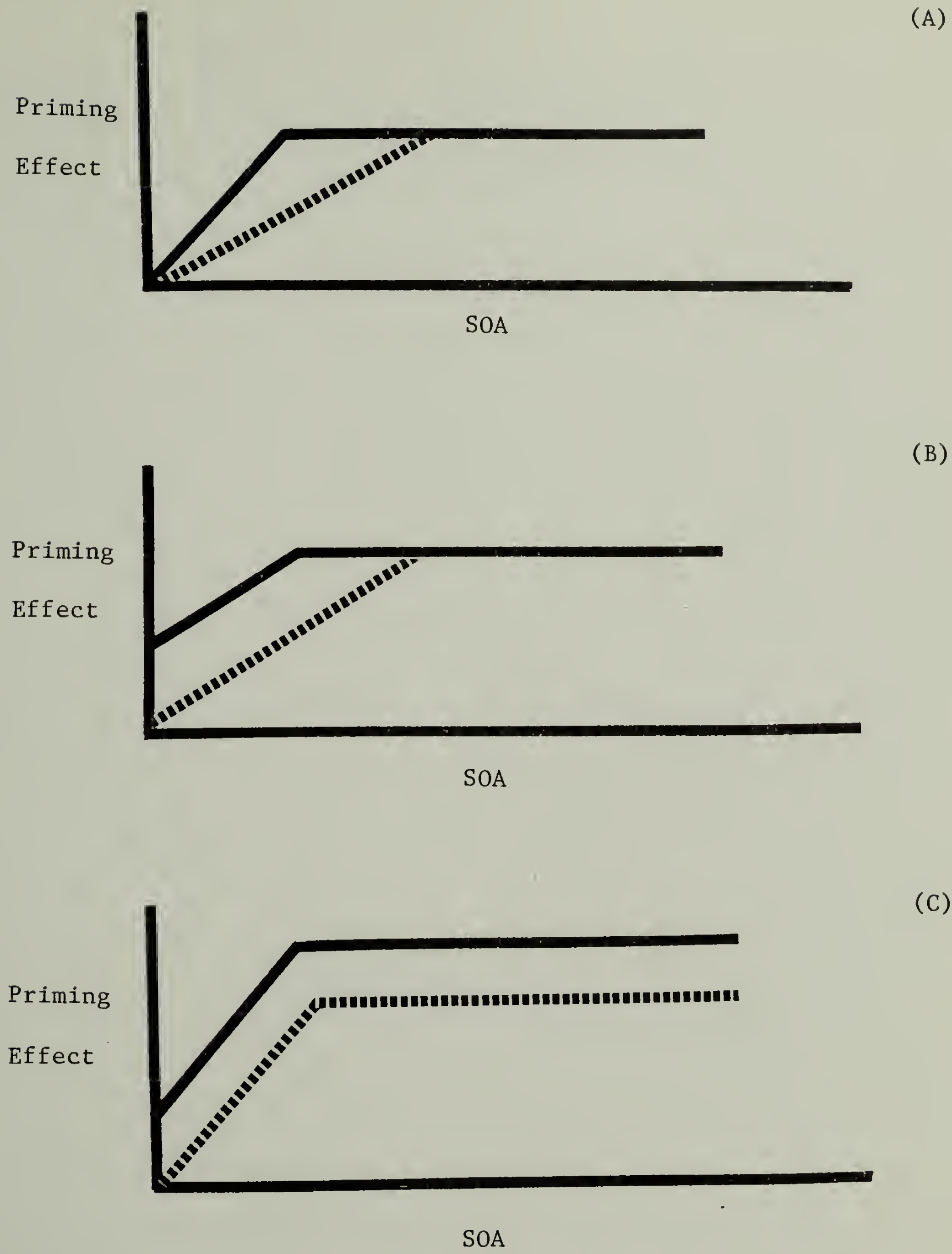

Figure 8. Predicted effects on priming of SOA and associative strength. Predictions are presented separately for the Rate Model (A), Distance Model (B), and Threshold Model (C). Solid lines indicate a strong association and dashed lines indicate a weak association.

"subset/superset" pathway -- serves as the source of activation of the probe for both strong and weak associates. In contrast, the Threshold Model proposes that the activation process is of equal duration for strong and weak associates. The Threshold Model predicts that the priming functions for the strong and weak associates will be parallel because it attributes the effects of strength and of SOA to two independent stages of processing -- activation and selection, respectively.

A final contrasting prediction concerns the effect of strength on the rate of change over SOAs in the magnitude of facilitation effects. The Distance and Threshold Models both hypothesize that activation rate is independent of strength, thus both predict that facilitation effects should accrue at the same rate for strongly and weakly associated prime-probe pairs (preasymptotically). In contrast, the Rate Model predicts that facilitation effects should increase at different rates for strong and for weak associates as SOA increases. This prediction follows from the Rate Model's claim that activation rate depends upon strength and from the observation that the rate of processing of the probe's memory structure will change after the exemplar word is presented relative to the processing rate during the interval between prime and probe presentation. Under the plausible assumption that the activation rate will be faster after probe presentation than before, the model predicts that facilitation effects will increase faster for strong than for weak associates (preasymptotically). The arguments underlying these predictions are analogous to those developed in Chapter IV and will not be repeated here.

Method

Materials. Category-exemplar word pairs were selected from two normative sources (Battig & Montague, 1969; Shapiro & Palermo, 1970) for use as prime-probe word pairs in the experiment. Pairs of exemplars differing in dominance were selected from 80 different semantic categories; no more than 6 pairs of exemplars were selected from a particular category. The complete list of 320 category-exemplar pairs is presented in Table 6 of Appendix A. An additional 38 high dominant and 38 low dominant pairs were generated for use as practice and filler items.

As in Experiment 1, the concern in selecting category-exemplar pairs in Experiment 2 was to establish an extreme manipulation of dominance. The mean percentage of subject producing the high dominant exemplars in response to their respective categories was 73.8 (SD = 15.87; Range = 40%-100%); the correspodning percentage for the low dominant exemplars was 7.6% (SD = 5.60; Range = 1%-48%). Dominance was again confounded with the frequency of usage of the exemplar word (Kucera & Francis, 1967): high dominant words are more frequent (M = 65.0; SD = 105.5) than low dominant words (M = 30.5; SD = 62.9). This confounding was allowed to permit as extreme a manipulation of dominance as possible. Finally, word length was approximately equated for the high dominant exemplars (M = 5.54; SD = 1.79) and low dominant exemplars (M = 5.53; SD = 1.68).

After all of the items had been generated, they were assigned to

9 blocks of 44 items each. Each block contained 22 high dominant exemplars and 22 low dominant exemplars. Half of the exemplars at each level of dominance were assigned to be cued by a neutral prime (i.e., the word "blank") and half were assigned to be cued by a category prime. Thus, a given exemplar was presented only once -- either with a neutral or category prime. The first block of stimuli was constructed from practice items and the first 4 items in the remaining test blocks were filler items which served as warm-up trials; thus, there were 40 critical items in each test block -- 10 representing each of the 4 possible prime-type x dominance conditions. Stimuli were assigned to blocks randomly and independently for each subject in the experiment. After the blocks had been constructed, they were then assigned to SOA conditions. Each successive pair of test blocks was assigned to a different SOA condition and the practice block was assigned to the same SOA condition as the intial two test blocks. Thus, the assignment of critical items to a given SOA x dominance x prime-type combination was different for each subject.

Design. Two subjects were assigned to each of the 24 possible sequences of SOA conditions, thus the design of the experiment was: 2 (high or low dominance) x 2 (neutral or category prime) x 4 (SOA = 150, 300, 450 or 600 msec) x 24 (sequence of SOAs) x 2 (subjects at a given level of the sequence variable). The variables of dominance, prime-type and SOA were manipulated within-subjects, while sequence was a between-subjects factor. Subjects was the only random effects variable in the design.

Procedure. Subjects were tested individually in an experimental session lasting less than one hour. Each subject was seated before a video display screen and microphone with each hand resting at a response lever. The sequence of events was the same on each trial: First, three "X's" appeared on the display screen to signal the start of the trial and to indicate where the prime word would appear. Next, after a 750 msec delay, the "X's" were erased and replaced with the prime. Finally, the probe word was presented two lines below the prime after a delay of 150, 300, 450 or 600 msec. Subjects were instructed to read the prime word silently when it appeared, then read the probe aloud as soon as it was presented. The contrast of the display screen was intentionally set at a low level and the letter of the probe were tightly packed together in order to retard the word recognition process. The purpose of the procedure was to magnify any priming effects that might occur in the task (Becker & Killion, 1977; Meyer, Schvaneveldt, & Ruddy, 1974).

The subject's vocal response to the probe word activated the voice key, causing the prime and probe to be erased from the screen and replaced by just the probe word. When the probe word was again presented, subjects pulled the right-hand response lever to indicate that they had made a correct response or they pulled the left-hand lever to indicate an error. Subjects were instructed to score a response as correct only if they named the probe word accurately without stuttering or otherwise prematurely activating the voice key, and only if the voice key was triggered as soon as they said the probe word. The screen erased as soon as the voice key was activated, so subjects knew if the voice key was activated prematurely or if it failed to activate. When the subject scored her response, the screen was erased and the next trial began after a three-second delay. A copy of the instructions is presented in Appendix B.

The sequence of trials within each block was randomized independently for each subject under the constraint that the first four trials of each block consist of the filler items. The assignment of items to blocks, the sequencing of trials within blocks, the presentation of stimuli and the timing of trials, and the collection of trial data were all controlled by a PDP-8E computer. RTs were measured to the nearest millisecond from the onset of the probe word until the voice key was triggered.

Subjects. All of the subjects were undergraduate students in psychology courses at the University of Massachusetts; 38 women and 18 men participated in the experiment. All subjects received experimental credit for their participation. Eight subjects were replaced: one subject was not a native English speaker; two subjects did not follow instructions properly; and the remaining subjects were lost due to equipment malfunctions.

Results and Discussion

Data analysis procedures. Each subject's mean RT for correct responses was calculated for each dominance x prime-type x SOA condition in the experiment. Similarly, the number of errors in each condition was computed for each subject. Each datapoint was thus based on a maximum of twenty observations. The RT and error data were submitted to separate trend analyses. Although the data were averaged over stimuli, the results of the tests of most treatment effects may be generalized to the population of items from which the stimuli were sampled because the assignment of items to a particular treatment combination was unique for each subject (Clark, 1973). The only exception is the test of the main effect of dominance on RTs (but not on priming effects), a test which is of little theoretical significance in this experiment. Unless noted otherwise, all reported results are significant beyond $p = .005$.

Findings. The results of Experiment 2 are presented in Table 2 and in Figure 9. Most of the important results of the experiment are apparent from Figure 9. The data meet most of the criteria for a definitive test of the three retrieval models. First, priming effects were observed: Subjects were faster to respond on category prime trials than on neutral prime trials, $F(1,24) = 152.34$, and subjects made fewer errors on category prime trials than on neutral prime trials, $F(1,24) = 34.91$. Second, priming effects were larger for strongly associated prime-probe pairs than for weakly associated pairs, $F(1,24) = 7.76$,

TABLE 2

REACTION TIMES (IN MSEC) AND PERCENTAGE ERRORS (IN PARENTHESES)
AS A FUNCTION OF EXPERIMENTAL CONDITION IN EXPERIMENT 2

Dominance	Prime	SOA 150	300	450	600	Mean
High	Neutral	729 (2.90)	694 (3.45)	676 (4.25)	668 (4.05)	692 (3.65)
	Category	691 (2.70)	634 (1.75)	608 (1.55)	597 (1.45)	633 (1.85)
Priming Effect		38 (0.20)	60 (1.70)	68 (2.70)	71 (2.60)	59 (1.80)
Low	Neutral	791 (9.15)	759 (9.80)	737 (7.30)	736 (8.15)	756 (8.60)
	Category	765 (5.20)	724 (4.70)	699 (5.00)	678 (5.40)	717 (5.05)
Priming Effect		26 (3.95)	35 (5.10)	38 (2.30)	58 (2.75)	39 (3.55)

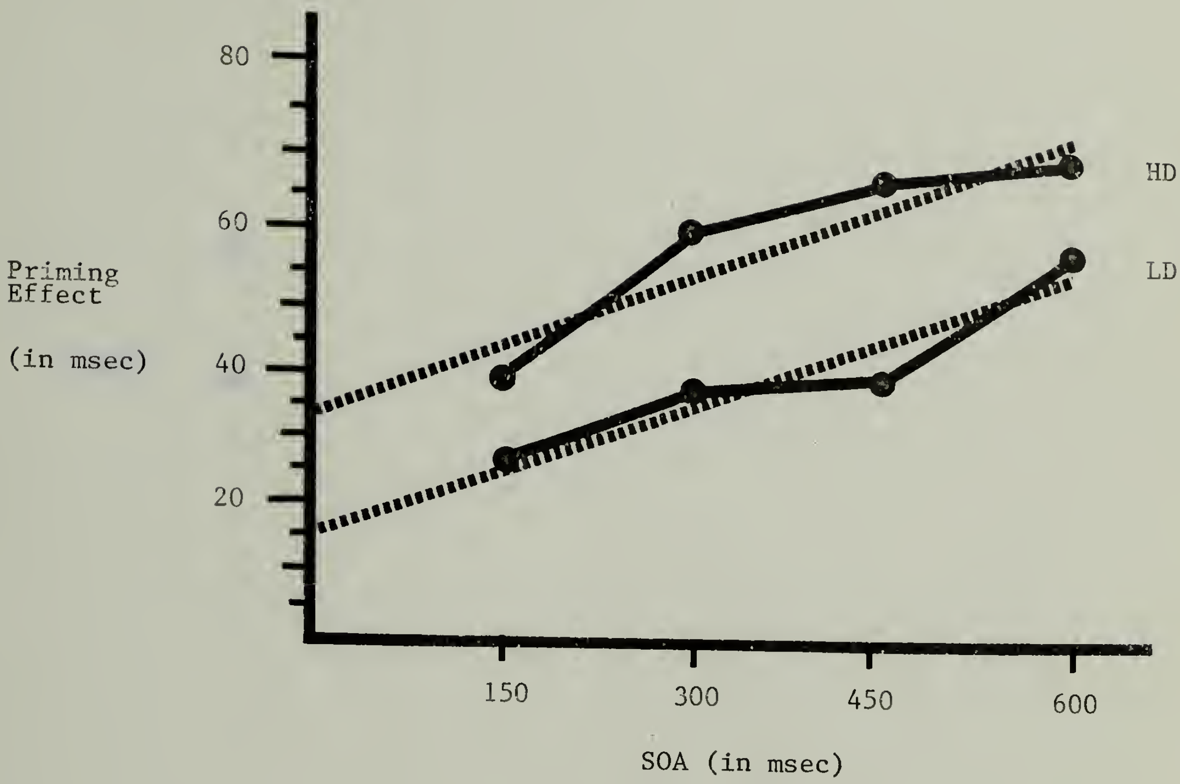

Figure 9. Priming effects on naming as a function of dominance and SOA. Data points are connected by solid lines; dotted lines represent the best-fitting functions for the high dominant (HD) and low dominant (LD) conditions.

$p < .025$. Third, facilitation effects increased monotonically as SOA increased; the linear component of the SOA effect on priming was significant, $F(1,24) = 11.82$. Unfortunately, the priming functions did not asymptote; the curvilinear componet of the SOA effect on priming was not significant, $F < 1$. No other effects on priming were reliable; the complete RT and error analyses are presented in Tables 15 and 16 in Appendix C.

Because the priming functions did not asymptote, the data do not stand alone as a definitive test of the models. On the other hand, the findings are consistent with those of Experiment 1 as far as they go. Most importantly, there was no evidence to support the Rate Model's claim that the rate of activation of a pathway is strength-determined. The trend analysis on the RT data suggested that the priming data is best fit by linear functions; the best fitting lines are plotted as dotted lines in Figure 9. It can be seen that the best fitting lines for the two conditions are nearly parallel: the regression equation for the high dominant items was: $Y = 33.3 + 10.4X$; the equation for the low dominant items was: $Y = 14.7 + 9.8X$. The test of the dominance x SOA(lin) interaction resulted in an F-value less than one; a difference in the slopes of approximately 13.4 msec would have resulted in a significant effect. Further, the dominance x SOA interaction was tested for all six possible pairs of SOAs with no hint of a reliably larger increase in priming over SOAs for high dominant items than for low dominant items. Thus, the present experiment is consistent with Experiment 1 in finding no evidence to support the hypothesis that activation spreads at a faster rate to strong associates than to weak associates of a prime.

Although the data from the naming task provide some reason to doubt the Rate Model's validity, they do not by themselves provide a basis for discriminating between the Distance Model and the Threshold Model. This is because the latter two models make contrasting predictions only with respect to the asymptotic portions of the priming functions and the data do not map out this part of the priming functions. Nevertheless, the results are encouraging because they provide further support for th Threshold Model even if they do not provide any further contradictory evidence with respect to the Distance Model.

Two unexpected results require some discussion. First, the error rates on low dominant items were quite high -- 8.6% in the neutral priming condition. This result appears jointly attributable to the general difficulty of recognizing words in the experiment (due to the low contrast of the display screen and the tight packing of letters) and to the low frequency of usage of many of the low dominant words. Second, subjects were 74 msec faster to respond to high dominant exemplars than to respond to low dominant exemplars, $F(1,24) = 365.46$. In particular, there was no reason to expect RTs to high and low dominant exemplars to differ in the neutral prime condition, but they did (64 msec effect). Again, this result may be due to the confounding of dominance with word frequency or with some other structural characteristc of the words (e.g., initial phoneme of the words). Although word frequency may be a less important determinant of performance in a naming task than in a lexical decision task (Scarborough et al., 1977), the fact that frequency is an important determinant of lexical decision performance (e.g., Becker, 1979) suggests that the dominance effect on RTs in the neutral priming condition is attributable to frequency effects on encoding. The confounding of dominance and frequency cannot be responsible for the priming effects observed in Experiment 2, however, because the available evidence from a lexical decision study suggest that priming effects should be larger for infrequent than for frequent words (Becker, 1979). Further, the results of a follow-up naming experiment conclusively rule out frequency as an important explanatory variable in Experiment 2.

Particular care was taken in the second naming experiment to match the high and low dominant words for length, frequency of usage and initial phoneme.[2] There were two important procedural differences between Experiment 2 and the second naming experiment: (1) Half of the prime-probe pairs in the second naming experiment were category-exemplar pairs and half were free associates (e.g., Table-Chair; Black-White). This procedure was followed in order to obtain sufficient numbers of stimuli for the experiment which met the control requirements. (2) The SOAs used in the second experiment were 200, 400, 600 and 800 msec, rather than 150, 300, 450 and 600 msec. The greater range of SOAs selected was to insure that the entire range of intervals in which automatic processes could be expected to operate was examined. The graph of the priming effects presented in Figure 10 demonstrates the similarity of the findings of the follow-up naming

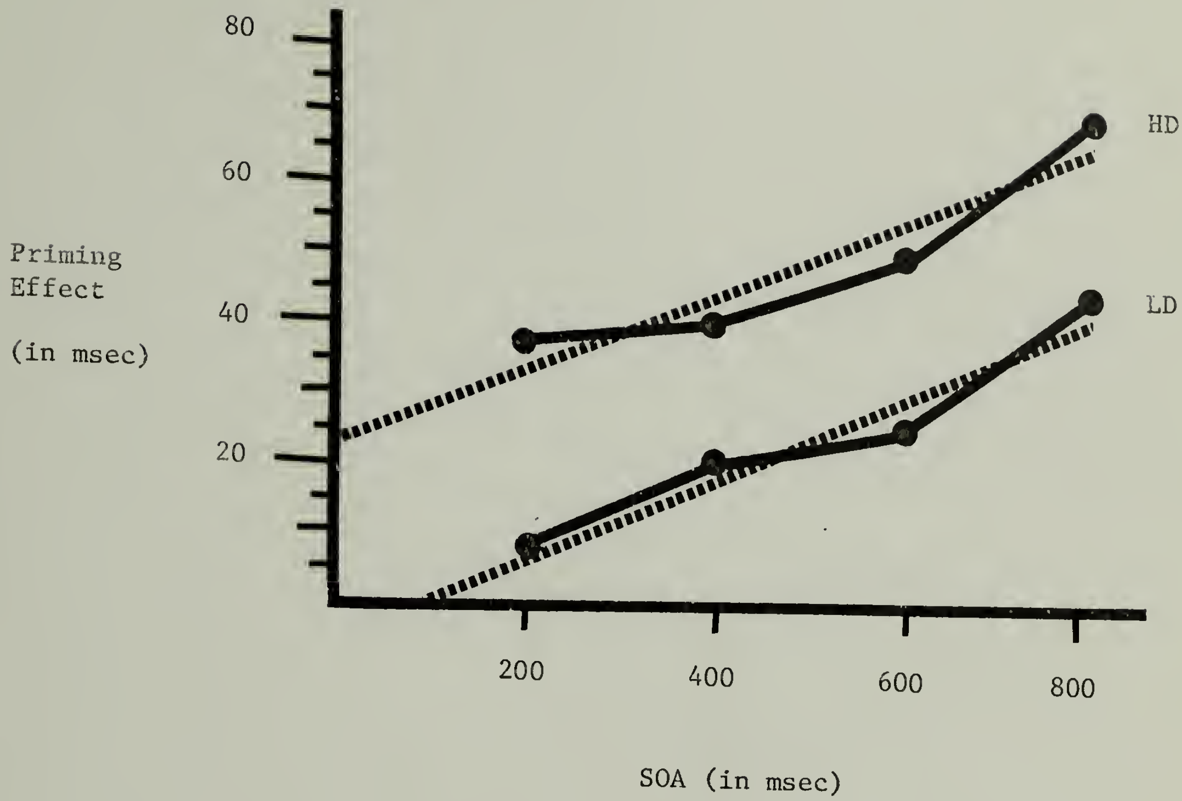

Figure 10. Priming effects in a naming task as a function of SOA and dominance. HD = high dominant; LD = low dominant; solid lines represent data and dotted lines represent the best-fitting lines.

experiment and the results of Experiment 2. First, priming effects were observed, $F(1,24) = 143.15$. Second, priming effects were an average of 26 msec greater for high than for low dominant items, $F(1.24) = 48.28$; this is to be compared with a 20 msec difference in Experiment 2. Third, facilitation effects increased as SOA increased by an average of 36 msec, $F(3,72) = 11.84$, compared with a 33 msec increase in Experiment 2. Finally, the relation between the priming effects and SOA was essentially linear and the slopes of the best-fitting lines computed for the high and low dominance conditions were nearly identical, as was the case for Experiment 2, [$F(1,24) = 18.73$ for SOA(lin); $F(1,24) = .03$ for the Dom x SOA(lin) interaction]. The care taken to match the high and low dominant words on several structural dimensions was rewarded by the finding that the difference in RTs to high versus low dominant items was only 6 msec in the neutral prime condition, compared with a 64 msec difference in Experiment 2. Thus, the results of the second naming experiment indicate that the findings of Experiment 2 are not attributable to the confounding of word frequency with dominance.

<u>Summary</u>. The findings of Experiment 2 are consistent with those of Experiment 1. Both experiments indicated that associates of a prime are activated at the same rate regardless of strength; this finding directly contradicts the Rate Model's hypothesis that activation rate is strength-determined. Although the priming functions for Experiment 2 did not asymptote nor did the functions for a follow-up naming experiment, neither did they show any tendency to converge as pre-

dicted by the Distance Model. On the other hand, the results of Experiment 1 and of both of the naming experiments presented in this chapter are consistent with the Threshold Model's prediction that the magnitude of the strength effect (on RTs or priming) should remain constant over SOAs. Thus, the findings support the Threshold Model's hypothesis that strength does not influence the duration of the activation process; rather, strength determines the speed with which an activated associative pathway will be selected for further processing. Experiment 3 presents a further test of the three retrieval models.

CHAPTER VI

EXPERIMENT 3: PRIMING A SENTENCE VERIFICATION DECISION

The third experiment has a dual purpose. First, it seeks to adapt the priming paradigm used in Experiment 2 to a sentence verification task. Previous investigations of priming using variations of the sentence verification task have employed a priming paradigm in which a response is required to the prime (Ashcraft, 1976; Collins & Quillian, 1970; Loftus, 1973; Loftus & Loftus, 1974). This procedure allows little control over the SOA and makes it difficult to specify the semantic relationship of the prime and probe (e.g., how is the semantic reltionship between two sentences to be measured?). Thus, Experiment 3 utilizes a priming paradigm with the same structure as the task used in the second experiment: A single word prime is presented on each trial, followed by a sentence which must be verified as a true or false statement. No overt response is required to the prime. The use of this paradigm will allow direct contact to be made between the results of priming a "semantic" decision and the extensive literature on the effects of priming in a "lexical" task such as naming or lexical decision. Further, it is hoped that semantic priming effects will be quite robust in the sentence verification task because the probe task requires extensive semantic processing relative to lexical tasks.

The second purpose of the experiment is to provide another test of the Threshold Model versus the Rate and Distance Models. Achievement of this goal depends, of course, on the success of the new experimental paradigm.

The experimental task is as follows. On each trial, either the name of a category or a neutral prime (the word "blank") is presented. After an interval of 200 or 600 msec, a brief phrase is presented which asserts some property of an exemplar of the category prime. For example, if the prime word is "Bird", the probe might be "Robin can fly." The subject's task is to evaluate the probe as a true or false statement and respond accordingly. The dependent variable of interest is the priming effect: the difference in RT between neutrally-primed and category-primed sentences in each condition. Only the results for true sentences will be analyzed. The independent variables are SOA, exemplar dominance and property dominance; the latter two variables refer to different aspects of the strength of the prime-probe relation. If the prime is the name of a category (e.g., Bird), the probe may be related to the prime in one of four ways: (1) the sentence is about a high dominant exemplar of the category and it asserts a property of the exemplar which is generally true of the category as well (e.g., Robin can fly); (2) the sentence is about a high dominant exemplar, but it asserts a property of the exemplar which is not a general property of the category (e.g., Robin has a redbreast); (3) the exemplar is low dominant and the property is high dominant with respect to the category prime (e.g., Duck has feathers); or (4) both the exemplar and property are low dominant (e.g., Duck can swim).

The process model for the experimental task is as follows. When a category prime is presented, the subject encodes the category name and activates associates of the category, including both exemplars and properties. Although the prime is logically irrelevant to performance of the probe task, activation from the prime should aid performance on the probe task by making more accessible information that is relevant to the evaluation of the probe. The neutral prime does not provide any information about the probe, but does serve to alert the subject. When a true probe sentence is presented, the subject encodes the sentence, retrieves the relation of the exemplar and property from memory, compares the retrieved relation with the asserted relation and responds "true" if they match; when the sentence is false, the subject is assumed to respond "false" based upon the retrieval of information that contradicts the probe sentence (Holyoak & Glass, 1975; Lorch, 1978). It is assumed that the maximal level of activation of the probe's memory structure by the category prime is below the level of activation necessary for retrieval of the exemplar-property relation.

What are the predictions of the three models concerning priming effects in the verification task? First, it must be noted that the manipulation of property dominance is such that there essentially is no direct association between the category prime and the property word in the probe sentence when property dominance is low. Thus, all of the models predict more facilitation for high than for low property dominance probes because high dominance probes have a source of activation from the category prime that is not available to low property dominance probes. The models differ, however, in their predictions of the effects of exemplar dominance and SOA. If it is assumed that automatic activation effects will reach their maximum within the 600 msec SOA, then the Rate and Distance Models both predict an interaction of exemplar dominance and SOA because both models assume that asymptotic activation is independent of strength: There should be more facilitation for high than for low dominant items at the 200 msec SOA, but not difference at the 600 msec SOA. In contrast, the Threshold Model predicts a constant effect of exemplar dominance across SOAs because of its claim that strength effects are attributable to selection, not activation. The predictions of the models are summarized graphically in Figure 11.

Method

Materials. Stimuli were constructed using the Ashcraft (1978b) property production norms. Ashcraft had subjects produce properties of seventeen semantic categories and of six instances from each of the categories. The categories and exemplars he used as stimuli were selected from the Battig and Montague (1969) norms. True items for the present experiment were constructed by first selecting category-exemplar pairs from the Ashcraft norms which differed in production frequency according to the Battig and Montague norms, then selecting property words to form category-exemplar-property triplets. Property words varied in the frequency with which they

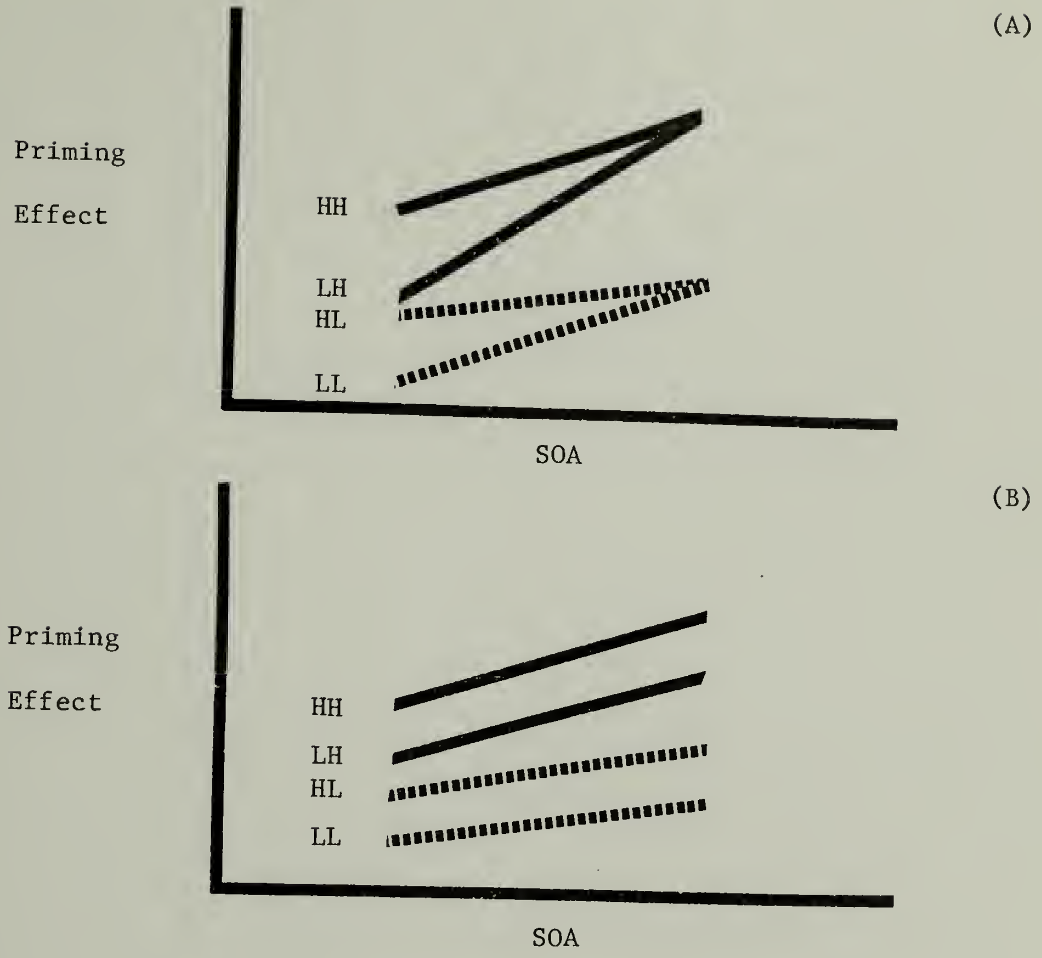

Figure 11. Predictions of the Rate and Distance Models (panel A) and of the Threshold Model (panel B) concerning how priming will depend upon SOA and exemplar and property dominance. The first letter of each label denotes the level of exemplar dominance and the second letter denotes the level of property dominance; H = high and L = low.

were produced as properties of the category they were paired with and they were selected to be paired with particular exemplars so that a true sentence could be constructed from the exemplar-property pair. A total of 96 exemplar-property pairs were generated and used to construct true sentences. When the sentences were paired with their category primes, there were 24 sentences representing each of the 4 possible exemplar dominance x property dominance conditions. The complete list of critical true sentences is presented in Table 7 of Appendix A. An additional 32 true items were generated for use as practice stimuli.

The characteristics of the critical true items are summarized as a function of condition in Table 3. "Sentence dominance" refers to the frequency with which the property word in the sentence was produced in response to the exemplar word (Ashcraft, 1978b). Care was taken to equate sentence dominance for the four exemplar dominance x property dominance conditions because sentence dominance is established to have a potent effect on performance in the sentence verification task (e.g., Ashcraft, 1978a; Conrad, 1972; Glass et al., 1974). It was impossible to control the frequency of usage of the exemplar and property words across conditions given the desire to control sentence dominance and the limited pool of items from which stimuli could be generated.

After the true items had been generated, false sentences were constructed. Each false sentence asserted a property of some exemplar which was not generally true (e.g., Tiger has spots; Penguin

TABLE 3

CHARACTERISTICS OF THE CRITICAL TRUE ITEMS IN EXPERIMENT 3

Exemplar, Property Dominance		Dominance of: Exemplar	Property	Sentence	Word Frequency Exemplar	Property
High, High	M =	68.4%	45.8%	44.6%	82.5	81.3
	SD =	21.2	13.8	21.0	158.0	113.4
High, Low	M =	71.0%	3.8%	44.1%	66.7	118.6
	SD =	20.4	5.1	17.4	139.6	162.3
Low, High	M =	9.1%	43.0%	43.9%	13.2	61.8
	SD =	5.9	18.8	20.1	14.4	69.7
Low, Low	M =	8.7%	2.8%	43.9%	11.9	110.0
	SD =	7.8	4.6	15.9	12.3	190.6

can fly). The false items were also generated using the Ashcraft norms: The category primes for the true and false sentences were the same and many of the exemplars were shared also. The exemplar dominance of the false sentences was varied and some attempt was made to vary property dominance as well in order to maximize the similarity of the true and false items with respect to item characteristics. The false items used in the test blocks of the experiment are presented in Table 7 of Appendix A; an additional 32 items were constructed for use in the practice block.

After the items had been generated, they were assigned to lists. Each list consisted of 2 practice blocks and 12 test blocks of 32 items each. Each block consisted of 16 true and 16 false items; in each block, there was one item of each truth-value representing each of the 16 SOA x prime-type x exemplar dominance x property dominance conditions in the experiment. List 1 was constructed by randomly assigning the 96 critical true items and the corresponding false items to each of the first 6 test blocks under the constraint that each of the 16 experimental conditions had to be represented once in each block. The last 6 test blocks of List 1 were then constructed by reversing the assignment of items to prime-type of the first 6 blocks. After List 1 was constructed, three other lists were generated from List 1: List 2 simply reversed the prime-type assignments of List 1, so the first 6 blocks of List 1 became the last 6 blocks of List 2 and the last 6 blocks of the first list became the first 6 blocks of the second list; List 3 reversed the assignments of items to SOA conditions relative to List 1; and List 4 reversed the SOA assignments of List 2. Thus, across the 4 lists of the experiment, each item appeared in each SOA x prime-type condition in both the first and second half of a list.

Design. Fourteen subjects were assigned at random to each of the four lists described above. Also, in addition to the experimental variables of interest, a variable of "practice" can be identified (i.e., first versus last six blocks in the list). Thus, the complete design of the experiment is: 2 (high or low exemplar dominace) x 2 (high or low property dominance) x 2 (category or neutral prime) x 2 (200 or 600 msec SOA) x 2 (levels of practice) x 4 (lists) x 14 (subjects nested within lists). "Lists" was the only between-subjects variable and subjects was the only random effects variable.

Procedure. Subjects were tested individually in an experimental session lasting less than one hour. Each subject was seated before a video display screen with each hand resting at a response lever. The sequence of events on each trial was essentially the same as in the previous experiments: First, three "X's" appeared on the display screen to signal the start of the trial and to indicate where the prime word would appear. Next, the "X's" were erased after a 750 msec interval and were replaced by the prime. The prime was erased after 200 msec and a sentence was presented directed below where the prime had been either immediately after the prime was erased (i.e., 200 msec SOA) or after a 400 msec delay (i.e., 600 msec SOA). Subjects were instructed to read the sentence silently, then decide whether the sentence was generally true or generally false and respond by pulling the right-hand lever to indicate "true" and the left lever to indicate "false." The screen was erased when the subject responded. If the response was correct, the next trial began automatically after a three-second delay; if the response was incorrect, "ERROR" appeared on the screen and the intertrial interval did not begin until the subject pulled a response lever to indicate that she wanted to continue. Subjects were instructed to respond as quickly as they were able to consistent with high accuracy. A copy of the complete instructions is presented in Appendix B.

A PDP-8E computer randomized the sequence of trials within each block independently for each subject; the order of test blocks within the first and second half of the experiment was also determined randomly and independently for each subject. RT was measured to the nearest millisecond from the onset of the probe sentence until a response lever was pulled. The computer controlled all aspects of the presentation of stimuli, the timing of trial events, and the collection of data.

Subjects. All of the subjects were undergraduate students in psychology courses at the University of Massachusetts; 41 women and 19 men participated in the experiment. All subjects received experimental credit for their participation. The data of four subjects was lost due to experimenter error.

Results and Discussion

Data analysis procedures. Each subject's mean RT and total number of errors was calculated for each condition in the experiment. Each datapoint was thus based on a maximum of six observations. The RT and error data were analyzed separately; only the data for the critical true items were analyzed. Because the assignment of items to SOA x prime-type conditions was counterbalanced across lists, the generality across items of a particular treatment effect could be assessed by examining whether the effect was the same across all lists.

Findings. The results for the critical true items are presented in Table 4; the means presented in Table 4 are collapsed across levels of practice and lists. The corresponding results for the false items are presented in Table 18 in Appendix D.

Summarizing the data presented in Table 4, there was a priming effect on RTs: Subjects were generally faster to respond on category prime trials than on neutral prime trials, $F(1,52) = 14.46$, $p < .001$. Second, as expected, priming facilitation was greater for the high property dominance condition than for the low property dominance condition, $F(1,52) = 17.03$, $p < .001$. Third, there was a tendency for facilitation effects to be larger at the 600 msec SOA

TABLE 4

MEAN REACTION TIMES (IN MSEC) AND PERCENTAGE ERRORS (IN PARENTHESES) AS A FUNCTION OF EXPERIMENTAL CONDITION FOR TRUE ITEMS IN EXPERIMENT 3

SOA = 200 msec

Exemplar Dominance Property Dominance		High High	High Low	Low High	Low Low	Mean
Prime	Neutral	1105 (4.02)	1080 (3.72)	1095 (3.57)	1123 (4.61)	1101 (3.98)
	Category	1059 (4.61)	1092 (4.32)	1070 (4.32)	1128 (5.65)	1087 (4.73)
Priming Effect		46 (-0.59)	-12 (-0.60)	25 (-0.75)	-5 (-1.04)	14 (-0.75)

SOA = 600 msec

Exemplar Dominance: Property Dominance:		High High	High Low	Low High	Low Low	Mean
Prime	Neutral	1041 (4.46)	1057 (3.87)	1071 (3.87)	1106 (4.32)	1069 (4.13)
	Category	987 (5.51)	1048 (4.91)	1025 (2.98)	1094 (4.61)	1039 (4.50)
Priming Effect		54 (-1.05)	9 (-1.04)	46 (0.89)	12 (-0.29)	30 (-0.37)

than at the 200 msec SOA, but this effect was not reliable, $F(1,52) = 2.69$, $p = .107$. No other effects on priming of any theoretical interest were significant. In particular, there was no effect of exemplar dominance on the magnitude of priming effects, $F < 1$, nor was there any tendency for the effects of exemplar dominance on priming to vary over SOAs, $F < 1$.

The data of Experiment 3 do not permit a test of the three models. Although priming effects were observed, the additional finding that the magnitude of priming effects varied over lists suggests that the result may be of limited generality, $F(3,52) = 3.65$, $p = .018$: the effect varied from 46 msec to -7 msec across lists. Further, there was evidence that the facilitation effect on RTs is attributable to a speed/accuracy tradeoff; subjects made more errors in the category prime condition than in the neutral prime condition, although the effect was not reliable, $F(1,52) = 2.96$, $p = .092$. There was also evidence that the effect of property dominance on priming is of limited generality; the interaction of property dominance and lists was significant, $F(1,52) = 3.14$, $p = .033$. Finally, the failure to find an effect of exemplar dominance on the magnitude of priming effects is contrary to the predictions of all three models. The failure to find an effect of exemplar dominance is surprising in the context of previous demonstrations of large priming effects on sentence verification performance (Ashcraft, 1976; Collins & Quillian, 1970). A potentially important procedural difference between the present experiment and previous investigations is that the previous studies utilized a different priming event: Subjects in the Ashcraft and in the Collins and Quillian experiments were presented a sentence as a prime and were required to make an overt verification response to the prime.

Summary. While priming effects were observed in the sentence verification task, the effects were small and of questionable generality. Further, there was no reliable increase in facilitation effects over the SOAs investigated nor was there an effect of exemplar dominance. Thus, the findings of Experiment 3 do not permit a test of the models under investigation and the task of discriminating the Rate, Distance and Threshold Models falls to the initial two experiments reported.

CHAPTER VII

GENERAL DISCUSSION

The final chapter will serve several interrelated purposes: We will consider the important accomplishments of the thesis; we will examine the implications of the empirical findings for the three retrieval models under consideration and will consider the nature of the retrieval process suggested by those findings; and we will evaluate the general theoretical context within which the Rate, Distance and Threshold Models were developed and have been judged. The discussion will focus on the results of the categorization experiment presented in Chapter IV and on the findings of the two naming experiments presented in Chapter V.

Establishment of Functional Descriptions

One important accomplishment of the experiments reported in the fourth and fifth chapters is that they establish the existence of an orderly relation between SOA and the dependent variable (RT or priming) for the two experimental paradigms employed. The reaction time data of Experiment 1 were well described by a simple orthogonal polynominal function of the form: $\hat{Y} = B_0 + B_1X + B_2X^2$, where B_0 equals the mean RT across levels of SOA and its value depends upon pathway strength; B_1 and B_2 are the coefficients of the linear and quadratic components of the function, respectively; and X denotes the value of the SOA. When separate functions were fit to the high and low dominant items of the first experiment, the high dominant function accounted for 98.1% of the variance in the SOA condition means and the low dominant function accounted for 96.8% of the variance. Similarly, the priming effects data for both naming experiments reported in Chapter V were well fit by a linear function over the range of SOAs investigated in those experiments (i.e., from 150 to 800 msec). A linear function accounted for 84.8% of the variance in the SOA condition means for the high dominant items of the first naming experiment and for 88.2% of the variance in the second naming experiment; a linear function accounted for 91.2% of the variance in the condition means for the low dominant items of the first naming experiment and for 96.4% of the variance in the follow-up naming experiment. Thus, the findings of Experiments 1 and 2 establish orderly relations between RT and SOA for the categorization task and between priming and SOA for the naming task; these functional descriptions may, in turn, be used as a basis for evaluating any model of retrieval which generates predictions for these experimental situations (Bush & Mosteller, 1955).

Theoretical Significance of Findings

In this section, we will further consider the reasons for the successes and failures of the Rate, Distance and Threshold Models in accounting for the findings reported in Chapter IV and Chapter V. The goal of this discussion is to more carefully specify the nature of the retrieval process suggested by the results reported in the fourth and fifth chapters. We will begin by briefly reviewing the theoretical context within which our conclusions are drawn, then evaluating each of the three retrieval models in turn.

The theoretical framework. The Rate, Distance and Threshold Models were all developed within the same theoretical framework: information was assumed to be represented in memory as a network of concept-nodes connected by labeled, strength-valued pathways. The basis of strength-value assignments is a matter of long theoretical debate (Anderson & Bower, 1973) and was left unspecified except to assume that the operational definition of strength used throughout (i.e., dominance) is an indirect measure of strength. All three models also adopted a spreading activation process as their basic search mechanism and assumed that retrieval consists of a two-stage process of activation and selection of pathways. Each model represents an hypothesis about how strength controls the processing of associative pathways during retrieval. The Rate Model proposed that strength determines the rate at which a pathway is activated to some threshold required for selection; the Distance Model proposed that strenth determines the amount of activation required to activate a pathway to threshold. Thus, the Rate and Distance Models both hypothesize that strength influences the duration of the activation process and thereby the duration of the retrieval process. The Threshold Model proposed that all pathways are activated at the same speed, but that strong paths are activated to a higher asymptote and thus are selected and retrieved faster than weak paths.

The experimental tests of the three models rested on four assumptions. First, Experiments 1 and 2 both utilized a priming paradigm to test the models, thus both experiments implicitly assume that a common spreading activation process underlies priming and search processes. This assumption is justified on two grounds: (1) current theoretical statements subscribe to this assumption (e.g., Anderson, 1976; Collins & Loftus, 1975); and (2) empirical results from priming paradigms are quite consistent in demonstrating the hypothesized properties of the spreading activation process assumed to underly search (see the review of the priming literature presented in Chapter III). Second, it is assumed that SOA affects the activation process but not the selection process. Third, the process models presented for the categorization task and for the naming task both assumed that priming effects observed in both experimental situations reflect the level of activation of a <u>single</u> associative pathway connecting the prime and probe stimulus (i.e., the "subset/superset" relation between the prime and probe). Finally, it has been assumed throughout that strength affects the duration of the retrieval process; supporting evidence for this assumption was presented in Chapter III.

The following evluations of the Rate, Distance and Threshold Models assume the theoretical framework summarized above.

The Rate Model. The Rate Model is unable to explain the finding that RTs to high and low dominant items asymptoted at different levels in the categorization experiment because the model attributes strength effects to differences in the duration of the activation process and activation of even weak pathways should have been complete at the longer SOAs of Experiment 1. The model also cannot account for the results that RT decreased at the same rate (preasymptotically) for high and low dominant items as SOA increased in Experiment 1; nor can it handle the finding that priming effects increased over SOAs at the same rate as a function of dominance in Experiment 2. The model predicted that priming effects would build at a faster rate for high dominant items because it hypothesizes a faster activation rate for strong than for weak pathways. Thus, the findings contradict the Rate Model's claim that strength controls the activation process. This conclusion is an important one because the Rate Model represents the currently dominant theoretical position in the literature (Anderson, 1976; Collins & Loftus, 1975; Hayes-Roth, 1977). The competitive search process proposed by models such as ACT does represent a viable model of the selection process, however, as will be discussed in the section below on the Threshold Model.

The Distance Model. The rejection of the Distance Model hinges on the critical result from Experiment 1 that the low dominant RT function asymptoted at a higher RT than the high dominant function: Because the Distance Model hypothesizes that the activation process will be longer for low than for high dominant items but that all pathways should be activated to the same level given sufficient time, it predicted that the high and low dominant RT functions would asymptote at the same level. Again, the implication of this result is that the duration of the activation process is independent of strength.

Although the class of Distance Models may be rejected based on the findings of Experiment 1, specific versions of the general model may be modifiable in ways which bring them into accord with the empirical results. In particular, the classification of the HAM model (Anderson & Bower, 1973) as a Distance Model was somewhat arbitrary. In classifying HAM as a Distance Model, the processes of retrieving a GET-list and scanning the list contents were interpreted as subprocesses of the activation stage of processing. An alternative interpretation of the model is that retrieval of a GET-list corresponds to the activation process, while the process of scanning the contents of the GET-list corresponds to the selection mechanism. Under this interpretation, all pathways are activated at the same speed because all pathways are contained on the GET-list; the activation levels of paths depend upon strength because strength may be interpreted as serial position in the GET-list according to HAM. Thus, HAM (and presumably other category-search models) might as readily be assigned to the Threshold Model class as to the Distance Model class. The important observation here is that the specific model be given an interpretation consistent with the Threshold Model; that is, the process upon which strength is hypothesized to operate must be identified as the selection process, not the activation process.

The Threshold Model. The Threshold Model accounts for the parallel RT functions of Experiment 1 and for the parallel priming functions of Experiment 2 and the follow-up naming experiment because it attributes the effects of SOA and strength to two independent subprocesses of retrieval -- activation and selection, respectively. There are at least two important implications of adopting the Threshold Model as a viable model of the retrieval process: (1) The Threshold Model emphasizes the automatic nature of the activation process; and (2) The model shifts the burden of explanation of empirical results from the activation process to the selection process and thus calls for further specification of the characteristics of the selection mechanism.

Automaticity of the activation process. Although strength is a primary determinant of retrieval speed, the unexpected conclusion from Experiments 1 and 2 is that strength has little or no effect on the duration of the activation process. This result suggests that the activation process is highly automatic in the sense of not being under the control of strength (or any other variable that has been identified): If an associative connection exists between two concept-nodes, then that pathway will be made available for selection at a speed which is independent of its strength. Note that the term "automatic" as employed here does not imply an unlimited capacity process (Posner & Snyder, 1974), although an unlimited capacity model is one possible realization of the Threshold Model (e.g., Wickelgren, 1976). Rather, the sense in which "automatic" is being used is closer to the definition suggested by Shiffrin and Schneider (1977; Schneider & Shiffrin, 1977) as entailing a process that is an inevitable consequence of some triggering stimulus event.

The claim being presented is that the result of attending to some concept is that all direct associative connections of the corresponding concept-node are activated simultaneously at the same speed. This claim amounts to the hypothesis that the set of direct connections of a concept-node reporesents a functional level of memory structure which is distinct from the level of the individual associative pathways. Thus, one appropriate metaphor for the activation process would be that it corresponds to the retrieval of a file (or schema) of information about the concept (Norman & Bobrow, 1979).[3] A complementary process-oriented interpretation of this hyothesis is that the activation process represents a "global" processing mechanism or a "preprocessor" which is responsible for orienting subsequent "focal" processes to the appropriate information necessary to perform some task (Neisser, 1967). Thus, according to the Threshold Model, the activation process serves to define the appropriate "search set" for the selection process (Perlmutter, Harsip, & Myers, 1976; Shiffrin, 1970).

<u>Selection mechanisms</u>. Continuing the analogy of the activation process to the retrieval of a computer file into an active "workspace" in memory, the selection process is responsible for a more

detailed examination of the contents of the retrieved file of pathways. The selection mechanism corresponds, if you will, to a "pointer" which may be set to any "line" (i.e., pathway) within the computer file to permit an evaluation of the contents at that location. How does this process of selection work?

The Threshold Model assumes that pathways are activated to a level which depends upon pathway strength -- strong paths are activated to a higher asymptote than weak paths. The selection process is sensitive to the activation level of a path, with strongly activated paths being selected faster than weakly activated paths. A couple of algorithms provide possible rules for selection based upon activation level. One rule has already been suggested in the earlier discussion of HAM (Anderson & Bower, 1973): The selection mechanism might consist of a serial scan of activated paths where the order of scanning is determined by the relative activation levels of the pathways in the search set. An alternative algorithm for selection corresponds to the competitive-search process of Rate Models such as the ACT model (Anderson, 1976). According to this rule, the selection process may be viewed as a process of drawing pathways from the search set at random and with replacement; the probability that a given path will be selected on a particular draw is given by its activation level relative to the sum of the activation levels of all paths in the search set (Perlmutter et al., 1976; Shiffrin, 1970). Thus, according to the Threshold Model, the Rate and Distance Models actually represent alternative models of the selection process, rather than models of the activation process.

Generality of Conclusions

The conclusions drawn in the preceding sections are, of course, limited by the assumptions on which they are based. Three assumptions that might be challenged are: (1) that strength effects are localized at retrieval; (2) that a common spreading activation process underlies both priming and search; and (3) that the priming effects observed in the categorization experiment and in the naming experiments reflect the level of activation of a single associative pathway between the prime and probe. These assumptions will be briefly discussed in turn.

The assumption that strength affects retrieval might be challenged; indeed, feature theories hypothesize that strength effects are localized at comparison processes operating subsequent to retrieval in the categorization task (McCloskey & Glucksberg, 1979; Smith et al., 1974a; 1974b). The assumption seems well supported, however, by the ability of retrieval models to account for strength effects and interference effects from a wide variety of experimental tasks (see Chapter III). Evidence is also available to support the claim that strength affects the duration of the retrieval process in the categorization task in particular (Lorch, Note 2). Nevertheless, even if the assumption is incorrect, the important conclusion that strength does not affect the duration of the activation process is still valid.

If it is assumed that priming and search represent fundamentally distinct processes, then the Rate and Distance Models can be rejected as models of priming but they may still be entertained as viable models of retrieval in search tasks. While this is a legitimate theoretical avenue to follow, it represents a less parsimonious approach than adopting the Threshold Model as an adequate explanation of results from both priming and search paradigms.

Perhaps most open to debate is the assumption that priming effects in Experiments 1 and 2 reflect the level of activation of a single pathway between the prime and probe; this assumption will be referred to as the "unidimensionality assumption." In fact, feature models assume that many (property-labeled) pathways between a category and exemplar will be activated, selected and evaluated in the normal course of making a categorization decision (McCloskey & Glucksberg, 1979; Smith et al., 1974a; 1974b); the logogen model similarly makes an assumption of "multidimensionality" in predicting priming effects for the naming task (Morton, 1969; 1970). What are the implications of adopting the multidimensionality assumption for the predictions of the Rate and Distance Models concerning categorization and naming performance? The answer is that it depends upon what dominance is assumed to measure under the multidimensionality assumption.

One commonly made assumption is that high dominant exemplars have more associative connections to their category than low dominant exemplars (McCloskey & Glucksberg, 19791 Rosch, 1975; Smith et al., 1974a; 1974b). Under this interpretation, the Rate and Distance Models correctly predict different asymptotic performance levels for the high and low dominance conditions of Experiments 1 and 2. The rationale for this prediction is the same for both models: The total amount of activation on pathways connecting the category and exemplar node will be greater for high than for low dominant items because there are more pathways in the former case than in the latter.

Although the predictions of the Rate and Distance Models concerning strength effects on asymptotic performance are straightforward under the multidimensionality assumption, the same is not true of their predictions of preasymptotic performance in the categorization and naming tasks. In order to derive predictions for the two models of how strength effects will vary as SOA increases, it is necessary to make assumptions about the number of category-exemplar paths and the distribution of strength across those paths as a function of dominance. The increase in theoretical complexity that results from adopting the multidimensionality assumption thus represents one argument for maintaining the unidimensionality assumption. A more telling argument against the Rate and Distance Models is based upon the observation that the predictions of the Threshold Model are unaltered by the adoption of the multidimensionality assumption. Because the model hypothesizes that the activation process is unaffected by strength, it does not matter what assumptions are made about the number of paths and the distribution of strength across paths connecting the category and exemplar nodes: SOA and dominance are still hypothesized to influence two independent retrieval processes -- activation and selection; thus, the model predicts independent effects of SOA and dominance under both the unidimensionality and the multidimensionality assumption. The ability of the Threshold Model to account for the empirical findings under both assumptions represents a strong argument for its adoption in preference to the Rate or Distance Model.

Summary

Neither the Rate Model nor the Distance Model was able to account for the independent effects of SOA and dominance observed in Experiments 1 and 2 because both models hypothesized that SOA and dominance would both influence the duration of the activation process of retrieval. The Threshold Model did predict independent effects of the two variables because it hypothesized that the variables influence the independent processes of activation and selection, rather than a common process. The adoption of the Threshold Model suggests a fundamentally different conception of the activation process than has usually been assumed: Rather than being a mechanism for the retrieval of individual associative connections, the activation process appears to be a pre-processing mechanism that makes an entire "file" of information available for closer scrutiny by a selection mechanism.

FOOTNOTES

1. The dominance of the true category-exemplar pairs was also confounded with lexical ambiguity: More low dominant items were ambiguous than high dominant items. The data were consequently reanalyzed excluding all ambiguous items. The results were identical to the results for the analysis on the complete set of items, thus ruling out lexical ambiguity as an important determinant of performance in Experiment 1. I would like to thank Lyn Frazier for pointing out this confounding and suggesting the reanalysis.

2. Keith Rayner pointed out the importance of controlling the initial phoneme of the exemplar words across levels of dominance.

3. I would like to thank Joseph V. DiCecco for suggesting this analogy.

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APPENDIX A

CRITICAL STIMULI FOR EXPERIMENTS 1, 2, AND 3

TABLE 5

CRITICAL STIMULI FOR EXPERIMENT 1

Category	True: High Dominance	True: Low Dominance	False: High Dominance	False: Low Dominance
Alcohol	Beer	Ale	Tea	Shoes
Alcohol	Whiskey	Brandy	Coffee	Soft
Animal	Dog	Fox	Vegetable	Island
Animal	Cat	Bull	Cracker	Boston
Appliance	Toaster	Fan	Kitchen	Green
Beverage	Milk	Cocoa	Cool	Teacher
Beverage	Coke	Sprite	Glass	Book
Bird	Robin	Chicken	Fly	Manmade
Bird	Sparrow	Duck	Wings	Captain
City	New York	Houston	Texas	Gills
Cloth	Cotton	Velvet	Woven	Father
Cloth	Wool	Denim	Coat	Fork
Clothing	Shirt	Vest	Warm	Noun
Clothing	Pants	Shorts	Nylon	Horse
Color	Blue	Gold	Bright	Trunk
Color	Red	Tan	Blind	Temple
Composer	Beethoven	Gershwin	Song	Lead
Country	France	Greece	City	Electric
Crime	Murder	Fraud	Prison	Head
Dance	Waltz	Minuet	Music	Tall
Disease	Cancer	Flu	Doctor	Satin
Distance	Mile	Block	Travel	Desk
Distance	Inch	Furlong	Airplane	Color
Dwelling	House	Cabin	Big	Bomb
Dwelling	Apartment	Castle	Roof	Mayor
Emotion	Love	Pity	Friend	Gin
Flower	Rose	Lilac	Petals	Hotel
Fruit	Apple	Lime	Vegetable	Ruler
Fruit	Orange	Fig	Fly	Swim
Fuel	Gasoline	Charcoal	Engine	Italy
Fuel	Oil	Steam	Tank	Legs
Fur	Mink	Seal	Coat	Garlic
Furniture	Chair	Chest	Bedroom	Priest
Furniture	Table	Bureau	House	Hill

TABLE 5 - continued

Category	True High Dominance	True Low Dominance	False High Dominance	False Low Dominance
Gem	Diamond	Garnet	Bracelet	Window
Gem	Ruby	Onyx	Steel	Bat
Genius	Einstein	Edison	Idiot	Snow
Insect	Fly	Moth	Bite	Mountain
Instrument	Piano	Organ	Play	Hair
Instrument	Drum	Bugle	Ballet	Dime
Jewelry	Ring	Brooch	Crystal	Beak
Jewelry	Necklace	Cufflink	China	Polka
Metal	Iron	Lead	Wood	Bean
Metal	Copper	Bronze	Emerald	Sweet
Money	Dollars	Check	Bank	Socks
Music	Jazz	Blues	Notes	Pine
Music	Classical	Opera	Cymbals	Yacht
Pet	Dog	Canary	Vulture	Bricks
Planet	Mars	Neptune	Sun	Measles
Profession	Doctor	Banker	Pay	Whale
Relative	Aunt	Son	Enemy	Crayon
Relative	Uncle	Daughter	Neighbor	Sound
Religion	Catholic	Islam	Church	Navy
Reptile	Snake	Iguana	Cow	Record
Rodent	Rat	Shrew	Cat	Moon
Royalty	King	Baron	Castle	Winter
Royalty	Queen	Duchess	Peasant	Plant
Science	Chemistry	Geology	English	Moves
Science	Physics	Genetics	Microscope	Lottery
Seafood	Lobster	Swordfish	Ocean	Saint
Seafood	Shrimp	Squid	Steak	Useful
Snake	Rattler	Viper	Frog	Technology
Sport	Football	Fishing	Athlete	Store
Sport	Baseball	Hunting	Compete	Pink
Time	Hour	Eon	Clock	Edible
Time	Minute	Score	Watch	Cobra
Tool	Hammer	Drill	Violin	Animal
Tool	Saw	File	Carpenter	Fur
Tree	Oak	Willow	Leaves	Tin
Tree	Maple	Palm	Branches	Radio
Utensil	Knife	Beater	Cook	Roots
Utensil	Spoon	Strainer	Kitchen	Noble

TABLE 5 - continued

Category	True: High Dominance	True: Low Dominance	False: High Dominance	False: Low Dominance
Vegetable	Carrot	Turnip	Fruit	Perform
Vegetable	Pea	Squash	Banana	Schubert
Vehicle	Car	Jeep	Wheels	Poison
Weapon	Knife	Tank	Kill	Paris
Weapon	Gun	Missle	Dangerous	Dress

TABLE 6

CRITICAL STIMULI FOR EXPERIMENT 2

	Dominance			Dominance	
Category	High	Low	Category	High	Low
Activity	Swimming	Singing	Animal	Dog	Fox
Animal	Cow	Bull	Animal	Horse	Moose
Appliance	Stove	Fan	Appliance	Toaster	Iron
Beverage	Milk	Cocoa	Beverage	Coke	Sprite
Bird	Robin	Duck	Bird	Sparrow	Chicken
City	New York	Houston	City	Chicago	Atlanta
Clergy	Priest	Monk	Cloth	Cotton	Velvet
Cloth	Wool	Lace	Cloth	Silk	Felt
Clothing	Shirt	Shorts	Clothing	Socks	Suit
Clothing	Pants	Vest	Color	Blue	Gold
Color	Red	Tan	Color	Green	Beige
Composer	Beethoven	Stravinsky	Composer	Bach	Strauss
Conqueror	Napoleon	Hannibal	Country	France	Greece
Country	England	Finland	Crime	Murder	Treason
Crime	Rape	Fraud	Dance	Waltz	Limbo
Day	Monday	Sunday	Dessert	Cake	Fudge
Dessert	Ice Cream	Brownies	Disease	Cancer	Rabies
Distance	Mile	Knot	Distance	Inch	Block
Drug	Marijuana	Dexedrine	Dwelling	House	Cabin
Dwelling	Apartment	Castle	Element	Oxygen	Mercury
Element	Hydrogen	Lithium	Emotion	Love	Rage
Emotion	Hate	Envy	Exercise	Running	Walking
Fish	Trout	Crab	Fish	Bass	Shad
Flower	Rose	Lilac	Flower	Tulip	Iris
Footwear	Shoes	Clogs	Footwear	Boots	Heels
Fruit	Apple	Lime	Fruit	Orange	Raisin
Fruit	Pear	Fig	Fuel	Gasoline	Propane
Fuel	Oil	Steam	Fuel	Coal	Peat
Fur	Mink	Seal	Fur	Rabbit	Ermine
Furniture	Chair	Chest	Furniture	Table	Divan
Furniture	Bed	Rug	Gem	Diamond	Garnet
Gem	Ruby	Onyx	Gem	Emerald	Amethyst
Genius	Einstein	Edison	Indian	Apache	Mohican
Insect	Fly	Moth	Insect	Ant	Tick
Instrument	Piano	Viola	Instrument	Drum	Bells

TABLE 6 - continued

Category	Dominance High	Dominance Low	Category	Dominance High	Dominance Low
Instrument	Trumpet	Bugle	Jam	Strawberry	Blackberry
Jewelry	Ring	Charm	Jewelry	Necklace	Cufflink
Jewelry	Bracelet	Pendant	Juice	Grape	Prune
Language	German	Latin	Language	Spanish	Swedish
Liquid	Water	Coffee	Liquor	Whiskey	Brandy
Liquor	Gin	Ale	Liquor	Vodka	Sherry
Meat	Beef	Deer	Meat	Pork	Liver
Metal	Iron	Carbon	Metal	Copper	Nickel
Metal	Steel	Bronze	Money	Dollar	Ruble
Money	Dime	Check	Month	June	August
Music	Jazz	Blues	Music	Classical	Opera
Novelist	Hemingway	Salinger	Ocean	Atlantic	Antarctic
Office	President	Alderman	Office	Senator	Sheriff
Painter	Picasso	Rockwell	Pet	Cat	Canary
Planet	Mars	Uranus	Planet	Venus	Neptune
Poet	Frost	Burns	Profession	Doctor	Banker
Profession	Lawyer	Farmer	Relative	Aunt	Wife
Relative	Uncle	Son	Relative	Father	Daughter
Religion	Catholic	Buddhist	Religion	Jewish	Moslem
Reptile	Snake	Toad	Reptile	Alligator	Chameleon
Rodent	Rat	Bat	Rodent	Mouse	Shrew
Royalty	King	Earl	Royalty	Queen	Count
Royalty	Prince	Lord	Science	Chemistry	Genetics
Science	Biology	Geology	Science	Zoology	Anatomy
Seafood	Lobster	Swordfish	Seafood	Shrimp	Squid
Seafood	Clams	Snail	Season	Summer	Autumn
Seasoning	Salt	Sage	Seasoning	Pepper	Ginger
Shape	Triangle	Polygon	Shape	Circle	Ellipse
Shape	Rectangle	Trapezoid	Ship	Sailboat	Clipper
Snake	Rattler	Viper	Snake	Cobra	Asp
Sport	Football	Hunting	Sport	Baseball	Softball
Sport	Tennis	Boxing	State	California	Minnesota
Time	Hour	Age	Time	Minute	Epoch
Time	Year	Night	Tool	Hammer	Crowbar
Tool	Saw	Axe	Tool	Nails	File
Toy	Doll	Top	Toy	Ball	Cards
Tree	Oak	Ash	Tree	Maple	Willow

TABLE 6 - continued

Category	Dominance High	Dominance Low	Category	Dominance High	Dominance Low
Tree	Elm	Fir	Utensil	Fork	Cup
Utensil	Knife	Glass	Utensil	Spoon	Tongs
University	Harvard	Purdue	Vegetable	Carrot	Turnip
Vegetable	Peas	Beets	Vegetable	Corn	Squash
Vehicle	Car	Van	Vehicle	Bus	Jeep
Vehicle	Airplane	Tractor	Weapon	Gun	Tank
Weather	Rain	Fog	Weather	Snow	Gale
Weather	Hurricane	Hailstorm	Wood	Pine	Teak

TABLE 7

CRITICAL STIMULI FOR EXPERIMENT 3

High Exemplar Dominance True Items			
High Property Dominance		Low Property Dominance	
Category	Sentence	Category	Sentence
Animal	Lion has fur.	Animal	Lion has a mane.
Animal	Horse has legs.	Beverage	Coffee is black.
Bird	Robin has wings.	Bird	Robin has redbreast.
Bird	Bluejay has feathers.	Bird	Sparrow is small.
Building	House has windows.	Building	House is a shelter.
Cloth	Cotton is soft.	Cloth	Cotton is white.
Cloth	Nylon is manmade.	Clothing	Shirt has a collar.
Clothing	Coat is warm.	Clothing	Dress has a hem.
Fish	Trout has gills.	Fish	Trout is edible.
Fish	Tuna can swim.	Fish	Salmon is food.
Flower	Rose has leaves.	Flower	Rose has thorns.
Flower	Daisy has stem.	Fruit	Apple has a core.
Fruit	Apple is sweet.	Fruit	Pear is green.
Fruit	Pear has juice.	Furniture	Chair has a seat.
Furniture	Table is wood.	Furniture	Table has a top.
Insect	Bee has wings.	Furniture	Sofa has cushions.
Insect	Spider is small.	Instrument	Drum is loud.
Instrument	Violin has strings.	Tool	Hammer has a handle.
Tool	Nail is metal.	Tool	Nail has a point.
Tree	Oak has branches.	Tree	Pine has needles.
Tree	Maple has roots.	Vegetable	Carrot is orange.
Vegetable	Carrot is edible.	Vegetable	Corn has a cob.
Vehicle	Car has wheels.	Vehicle	Airplane can fly.
Weapon	Gun is dangerous.	Weapon	Knife can cut.

TABLE 7 - continued

Low Exemplar Dominance True Items			
High Property Dominance		Low Property Dominance	
Category	Sentence	Category	Sentence
Animal	Rabbit has fur.	Animal	Rabbit has ears.
Animal	Lamb has legs.	Animal	Goat has hooves.
Bird	Duck has feathers.	Beverage	Milkshake is sweet.
Bird	Chicken has wings.	Beverage	Milkshake is creamy.
Bird	Owl can fly.	Bird	Duck can swim.
Building	Cabin is wood.	Building	Castle has a moat.
Building	Castle is big.	Cloth	Canvas is heavy.
Cloth	Burlap is woven.	Cloth	Burlap is rough.
Cloth	Flannel is warm.	Clothing	Belt has a buckle.
Clothing	Gloves are warm.	Clothing	Gloves have fingers.
Fish	Minnow can swim.	Fish	Shrimp is seafood.
Fish	Shrimp has a tail.	Fish	Minnow is small.
Flower	Lily has a stem.	Flower	Lilac is purple.
Flower	Lilac has a smell.	Fruit	Olive has a pit.
Fruit	Raisins are grapes.	Fruit	Raisins are wrinkled.
Furniture	Bench is wood.	Furniture	Bench has a seat.
Insect	Moth has wings.	Instrument	Tuba is brass.
Insect	Moth can fly.	Tool	Axe has a handle.
Instrument	Banjo has strings.	Tool	Ladder has steps.
Tool	Ladder is useful.	Tree	Bamboo is hollow.
Tool	Crowbar is metal.	Vegetable	Rice is white.
Vegetable	Rice is edible.	Vehicle	Raft can float.
Vehicle	Van has wheels.	Weapon	Whip is long.
Weapon	Poison can kill.	Weapon	Sword is sharp.

TABLE 7 - continued

High Exemplar Dominance False Items			
High Property Dominance		Low Property Dominance	
Category	Sentence	Category	Sentence
Animal	Horse is small.	Animal	Tiger has spots.
Animal	Lion is tame.	Animal	Cat is loud.
Beverage	Milk is carbonated.	Beverage	Coke is green.
Bird	Robin is blue.	Bird	Sparrow is big.
Bird	Eagle is small.	Bird	Bluejay is brown.
Building	House has elevators.	Building	House has a moat.
Cloth	Cotton is manmade.	Cloth	Nylon is grown.
Cloth	Silk is coarse.	Clothing	Shirt has legs.
Fish	Shark has scales.	Fish	Trout is dangerous.
Flower	Daisy is red.	Fish	Tuna is small.
Fruit	Orange is sour.	Flower	Tulip has thorns.
Fruit	Peach is red.	Flower	Rose is blue.
Furniture	Table has arms.	Fruit	Apple has a pit.
Furniture	Lamp has legs.	Fruit	Peach has a core.
Instrument	Drum has strings.	Furniture	Table has a mattress.
Instrument	Trumpet has keys.	Furniture	Bed has drawers.
Insect	Ant has wings.	Instrument	Violin has pedals.
Tool	Hammer is a machine.	Tool	Saw has a head.
Tool	Nail has a handle.	Tool	Nail has teeth.
Tree	Pine has leaves.	Tree	Maple has acorns.
Tree	Elm has fruit.	Tree	Oak has syrup.
Vegetable	Carrot has seeds.	Vegetable	Corn is bitter.
Vehicle	Bus has wings.	Vehicle	Truck has a pilot.
Weapon	Gun has a blade.	Weapon	Knife has a trigger.

TABLE 7 - continued

Low Exemplar Dominance False Items			
High Property Dominance		Low Property Dominance	
Category	Sentence	Category	Sentence
Animal	Mouse is big.	Animal	Bull has antlers.
Animal	Rabbit is loud.	Animal	Rabbit is fierce.
Beverage	Cocoa is cool.	Beverage	Cider has caffeine.
Bird	Duck has claws.	Bird	Chicken can swim.
Bird	Penguin can fly.	Bird	Ostrich is pink.
Building	Cabin is tall.	Building	Igloo has towers.
Cloth	Burlap is smooth.	Building	Dorm has a dungeon.
Clothing	Scarf has a zipper.	Cloth	Chiffon is heavy.
Clothing	Nylons have buttons.	Clothing	Nylons have pockets.
Fish	Shrimp has gills.	Fish	Minnow is big.
Fish	Shrimp has fins.	Fish	Flounder has claws.
Flower	Lilac is red.	Flower	Lilac has prickers.
Fruit	Raisins are green.	Fruit	Raisins are smooth.
Fruit	Lime is sweet.	Fruit	Olive is red.
Furniture	Rug has legs.	Furniture	Bench has springs.
Insect	Roach can fly.	Furniture	Mirror has a seat.
Instrument	Viola is metal.	Insect	Flea has a hive.
Tool	Sandpaper is metal.	Instrument	Organ is a horn.
Tree	Fir has leaves.	Tool	Ladder has a blade.
Vegetable	Beets are yellow.	Tool	File is smooth.
Vegetable	Rice is green.	Tree	Palm has needles.
Vehicle	Rocket has wheels.	Vegetable	Squash has a husk.
Vehicle	Raft has a motor.	Vegetable	Onions have kernels.
Weapon	Whip has a blade.	Weapon	Poison is safe.

APPENDIX B

INSTRUCTIONS FOR EXPERIMENTS 1, 2, AND 3

Instructions for Experiment 1

This is a study about how people retrieve information from their memories. On each trial in the experiment, the following events will occur: First, 3 "Xs" will appear on the TV screen to signal that the trial is beginning and to mark where the first word will appear. Next, after a short delay, the name of a category will replace the Xs. Finally, a word will appear directly below the category name. The time interval between presentation of the category and the word will vary between 0--the 2 words will sometimes be presented simultaneously--and a little over half a second. Your task is to read the category name to yourself as soon as it appears, then decide whether the word that follows it is a member of the category or not. If the word is a member of the category, respond "yes" by pulling the lever on your right towards you; if the word is not a member of the category, respond "no" by pulling the left-hand lever. For example, if the category is "State", you would respond "yes" to "Hawaii", "Florida", "Maine", etc.; while you would respond "no" to "Hartford", "bed", "river", etc. <u>It is important that you respond as quickly as you can without making errors</u>.

You will receive a total of 8 blocks of 50 trials each. The interval between presentation of the category and word will differ for each block, but it will be the same within a block. If your response on a trial is correct, the computer will automatically continue to the next trial. If you make an error, the word "ERROR" will appear and will remain on the screen until you signal that you want to continue by pulling either lever. Similarly, at the start of a block, the word "READY" will appear and you may then begin by pulling either lever. Finally, I should mention that there is a time-limit on responding: If you do not respond within 4 seconds of when the second word in a trial appears, "ERROR" will automatically appear. Four seconds will generally be much more time than necessary for you to make a response--the computer assumes you don't know what the correct response is if you can't respond within 4 seconds. In fact, if you encounter an item you don't know, please do <u>not</u> respond rather than guessing.

To summarize, pull the right-hand lever to respond "yes"; pull the left-hand lever to respond "no". Respond as quickly as you can on each trial while keeping errors to a minimum--you should not make more than 3 or 4 errors per block. Do you have any questions? When you are ready, please read and sign the informed consent form.

Instructions for Experiment 2

This experiment investigates how the context which precedes a simple task affects performance on that task. On each trial in the experiment, you will see the following series of events:

(1) First, three "Xs" will appear on the screen for a short interval of time to let you know that the trial is beginning.

(2) Next, a single word will replace the Xs on the screen. The word will either be the word "blank" or some other word. It is very important that you read this word silently to yourself when it appears since I am interested in what the effects of having to attend to this word will be. The word will be presented for a very brief period and it will quickly be followed by a second word, so it may be tempting to ignore the word altogether. Please resist any temptation to ignore the word and always attend to it.

(3) After the first word appears, a second word will be presented directly below it. If the first word is a word other than "blank", the second word will be related to it in some way. For example, if the first word had been "STATE", the second word might be "MAINE". When the second word appears, your task is simply to say the word aloud into the microphone as soon as you recognize the word. You should respond as quickly as you can without making errors because I am interested in how long it takes you to recognize and say the word.

(4) As soon as the microphone records your voice, the word will be erased and then it will be presented again with a question mark (e.g., MAINE?). The computer is asking you whether you said the word correctly. If that is the word you just said (i.e., if you didn't mispronounce the word or say another word entirely) and if you didn't stutter or say "um" or do anything else to trigger the microphone prematurely, then pull the lever on your right marked "yes"; if you made any kind of mistake in your response, pull the left-hand lever marked "no".

There will be 9 blocks of 44 trials each altogether. The whole experiment takes approximately 45 minutes to do. If you want to take a break at any point, feel free to take one between blocks.

To summarize, on each trial you will see a word followed by another word. You should always read the first word to yourself quickly, then say the second word aloud as soon as you can. Finally, score your response as correct by pulling the right lever and score it as incorrect by pulling the left lever. If you have any questions, please ask them. When you are ready to start, please read and sign the "Informed Consent Form".

Instructions for Experiment 3

This experiment investigates how the context which precedes a simple task affects performance on that task. On each trial in the experiment, you will see the following series of events:

(1) First, three "Xs" will appear on the screen for a short interval of time to let you know that the trial is beginning.

(2) Next, a single word will replace the Xs on the screen. The word will either be the name of a category or the word "blank." <u>It is very important that you say the word to yourself when it appears</u> since it is the effect of attending to this word that I am interested in. The word will be presented for a very brief period of time and it will quickly be followed by a sentence, so it may be tempting to ignore the word altogether. Please resist any such temptation to ignore the word and always say it to yourself.

(3) After the word is erased, a sentence will be presented directly below where the word had been. If the word had been the name of a category, the sentence will be about some exemplar of the category. For example, if the word had been "STATE", the sentence might be "Maine has mountains". When the sentence is presented, your task is to decide whether the statement is generally true or generally false. If the sentence is in general true, pull the lever on your right towards you; if the sentence is generally false, pull the lever on the left towards you. It is important

that you respond as soon as you make your decision because I am measuring how long it takes you to respond to each item. <u>You should respond as quickly as you can while still being accurate; you should not make more than 2 or 3 careless errors in each set of 32 items</u>. When you make a correct response, the screen will erase and the next trial will begin automatically; "ERROR" will appear if you respond incorrectly. When "ERROR" or "READY" is presented (at the start of a block of trials), pull either lever if you want to get going again. Altogether there are 14 blocks of 32 items each. The whole procedure takes between 45 and 55 minutes. If you need a break at any point, feel free to take one.

To summarize, on each trial you will see a word followed by a sentence. You should always say the word to yourself as quickly as you can, then decide whether the sentence which follows is true or false. Pull the right lever to respond "true" and the left lever to respond "false". If you have any questions, please ask them. When you are ready to start, please read and sign the "Informed Consent" form.

APPENDIX C

RESULTS OF STATISTICAL ANALYSES ON DATA FROM EXPERIMENTS 1, 2, AND 3

TABLE 8

TREND ANALYSIS ON RT DATA FOR TRUE ITEMS IN EXPERIMENT 1

SV	df	MS	F	p
Dominance	1	5,544,367	272.930	<.001
Error	48	20,314		
SOA	6	917,105	37.969	<.001
Error	288	24,154		
SOA (lin)	1	4,038,931	119.455	<.001
Error	48	33,811		
SOA (quad)	1	1,368,087	98.788	<.001
Error	48	13,849		
SOA (resid)	4	23,903	.983	
Error	192	24,316		
Dom x SOA	6	13,988	1.364	
Error	288	10,257		
D x SOA (lin)	1	10,521	.740	
Error	48	14,211		
D x SOA (quad)	1	25,537	3.019	.089
Error	48	8,458		
D x SOA (resid)	4	11,968	1.232	
Error	192	9,718		

TABLE 9

TREND ANALYSIS ON RT DATA FOR TRUE ITEMS INCLUDING ONLY THE FOUR SHORTEST SOAs OF EXPERIMENT 1

SV	df	MS	F	p
Dominance	1	3,128,572	209.770	<.001
Error	48	14,914		
SOA	3	1,003,526	43.976	<.001
Error	144	22,820		
SOA (lin)	1	2,833,281	142.340	<.001
Error	48	19,905		
SOA (curve)	2	88,649	3.652	.05
Dom x SOA	3	4,038	.378	
Error	144	10,669		
Dom x SOA (lin)	1	1,513	.112	
Error	48	13,464		
Dom x SOA (curve)	2	5,301	.572	
Error	96	9,271		

TABLE 10

RESULTS OF F-TESTS OF THE DOMINANCE x SOA INTERACTION FOR ALL POSSIBLE PAIRS OF SOAs: RT DATA FOR TRUE ITEMS IN EXPERIMENT 1

SOA Contrast	Effect	Error Term	F	p
0 vs 100	-20 msec	12,035	.433	.514
0 vs 200	-11 msec	10,699	.151	.700
0 vs 300	9 msec	15,023	.061	.806
0 vs 400	-42 msec	9,311	2.391	.129
0 vs 500	0 msec	11,473	.001	.982
0 vs 600	34 msec	19,418	.714	.402
100 vs 200	9 msec	9,632	.107	.745
100 vs 300	29 msec	7,311	1.437	.236
100 vs 400	-22 msec	8,011	.740	.394
100 vs 500	20 msec	6,564	.742	.393
100 vs 600	54 msec	11,764	3.069	.086
200 vs 300	20 msec	9,343	.530	.470
200 vs 400	-31 msec	8,143	1.463	.232
200 vs 500	11 msec	7,952	.178	.675
200 vs 600	45 msec	11,459	2.175	.147
300 vs 400	-51 msec	8,052	4.002	.051
300 vs 500	-9 msec	8,129	.132	.718
300 vs 600	25 msec	7,559	1.013	.319
400 vs 500	42 msec	10,256	2.101	.154
400 vs 600	76 msec	13,299	5.361	.025
500 vs 600	34 msec	9,995	1.446	.235

TABLE 11

RESULTS FOR F-TESTS FOR ALL PAIRWISE COMPARISONS OF SOAs CONDUCTED SEPARATELY FOR THE HIGH AND LOW DOMINANCE CONDITIONS OF EXPERIMENT 1: RT DATA FOR TRUE ITEMS

	High Dominance			Low Dominance		
Contrast	Effect	Error Term	F	Effect	Error Term	F
0 vs 100	123 msec	14,761	24.970**	143 msec	26,957	18.660**
0 vs 200	162 msec	9,831	65.714**	174 msec	19,153	38.656**
0 vs 300	246 msec	9,491	156.313**	237 msec	25,736	53.664**
0 vs 400	246 msec	11,496	130.343**	290 msec	22,715	90.672**
0 vs 500	261 msec	12,554	133.135**	262 msec	23,899	70.304**
0 vs 600	256 msec	15,300	104.693**	222 msec	39,059	30.925**
100 vs 200	40 msec	14,772	2.619	31 msec	20,216	1.131
100 vs 300	123 msec	10,730	34.785**	94 msec	22,585	9.614**
100 vs 400	125 msec	11,579	32.877**	147 msec	17,250	30.547**
100 vs 500	139 msec	12,109	38.828**	119 msec	22,264	15.477**
100 vs 600	133 msec	14,503	29.900**	79 msec	37,504	4.052*
200 vs 300	84 msec	11,364	15.102**	64 msec	15,334	6.461*
200 vs 400	85 msec	8,770	20.146**	116 msec	17,670	18.690**
200 vs 500	99 msec	13,654	17.513**	88 msec	18,046	10.524**
200 vs 600	93 msec	10,719	19.899**	48 msec	18,288	3.113
300 vs 400	1 msec	8,755	.004	53 msec	15,872	4.256*
300 vs 500	15 msec	12,395	.451	25 msec	19,447	.753
300 vs 600	10 msec	10,903	.208	-15 msec	14,695	.395

TABLE 11 - continued

	High Dominance			Low Dominance		
Contrast	Effect	Error Term	F	Effect	Error Term	F
400 vs 500	14 msec	12,453	.379	-28 msec	24,641	.783
400 vs 600	8 msec	11,600	.149	-68 msec	25,077	4.504*
500 vs 600	-6 msec	12,859	.057	-40 msec	25,617	1.518

$^{**}p < .005$
$^{*}p < .05$

TABLE 12

TREND ANALYSIS ON ERROR DATA FOR TRUE ITEMS IN EXPERIMENT 1

SV	df	MS	F	p
Dominance	1	121.751	208.455	<.001
Error	48	.584		
SOA	6	.182	.334	
Error	288	.545		
SOA (lin)	1	.036	.051	
Error	48	.720		
SOA (quad)	1	.004	.008	
Error	48	.560		
SOA (resid)	4	.262	.528	
Error	192	.497		
Dom x SOA	6	.448	.843	
Error	288	.531		
Dom x SOA (lin)	1	.071	.123	
Error	48	.583		
Dom x SOA (quad)	1	.409	.851	
Error	48	.480		
Dom x SOA (resid)	4	.552	1.039	
Error	192	.531		

TABLE 13

TREND ANALYSIS ON RT DATA FOR TRUE ITEMS IN EXPERIMENT 1

SV	df	MS	F	p
Dominance	1	3,556,944	141.323	.001
Error	48	25,169		
SOA	6	1,439,512	63.478	.001
Error	288	22,677		
SOA (lin)	1	6,695,893	224.682	.001
Error	48	29,802		
SOA (quad)	1	1,850,790	69.813	.001
Error	48	26,511		
SOA (resid)	4	22,598	1.133	
Error	192	19,938		
Dom x SOA	6	9,896	1.093	
Error	288	9,052		
Dom x SOA (lin)	1	23,940	2.380	
Error	48	10,058		
Dom x SOA (quad)	1	1,990	.216	
Error	48	9,228		
Dom x SOA (resid)	4	8,362	.955	
Error	192	8,757		

TABLE 14

TREND ANALYSIS ON ERROR DATA FOR FALSE ITEMS IN EXPERIMENT 1

SV	df	MS	F	p
Dominance	1	87.500	130.667	<.001
Error	48	.670		
SOA	6	.642	1.492	
Error	288	.430		
SOA (lin)	1	2.758	4.407	<.05
Error	48	.626		
SOA (quad)	1	.423	1.125	
Error	48	.376		
SOA (resid)	4	.168	.424	
Error	192	.395		
Dom x SOA	6	.439	1.168	
Error	288	.376		
Dom x SOA (lin)	1	2.391	6.618	=.013
Error	48	.361		
Dom x SOA (quad)	1	.064	.133	
Error	48	.482		
Dom x SOA (resid)	4	.044	.126	
Error	192	.353		

TABLE 15

TREND ANALYSIS ON RT DATA OF EXPERIMENT 2

SV	df	MS	F	p
Between-subjects	47			
Sequence	23	223,067	1.215	
Error	24	183,545		
Within-subjects				
Prime	1	465,019	152.336	<.001
Seq x P	23	4,284	1.404	
Error	24	3,053		
Dominance	1	1,055,837	365.459	<.001
Seq x Dom	23	5,205	1.802	
Error	24	2,889		
P x Dom	1	19,521	15.513	<.001
Seq x P x Dom	23	1,689	1.342	
Error	24	1,258		
SOA	3	208,117	28.614	<.001
Seq x SOA	69	9,968	1.370	
Error	72	7,273		
SOA (lin)	1	576,828	71.059	<.001
Error	24	8,118		
SOA (quad)	1	47,157	6.940	=.015
Error	24	6,795		
SOA (cubic)	1	368	.053	
Error	24	6,907		
P x SOA	3	8,395	4.744	=.004
Seq x P x SOA	69	2,363	1.335	
Error	72	1,770		
P x SOA (lin)	1	24,402	11.823	=.002
Error	24	2,064		
P x SOA (curve)	2	392	.242	
Error	48	1,623		

TABLE 15 - continued

SV	df	MS	F	p
Dom x SOA	3	876	.415	
Seq x Dom x SOA	69	1,702	.805	
Error	72	2,113		
Dom x SOA (lin)	1	794	.369	
Error	24	2,203		
Dom x SOA (curve)	2	918	.444	
Error	48	2,069		
P x Dom x SOA	3	881	.420	
Seq x P x Dom x SOA	69	1,794	.855	
Error	72	2,100		
P x Dom x SOA (lin)	1	23	.009	
Error	24	2,516		
P x Dom x SOA (quad)	1	2,494	1.169	
Error	24	2,134		
P x Dom x SOA (cubic)	1	125	.076	
Error	24	1,649		

TABLE 16

TREND ANALYSIS ON ERROR DATA OF EXPERIMENT 2

SV	df	MS	F	p
Between-subjects				
Sequence	23	2.699	.552	
Error	24	4.891		
Within-subjects				
Prime	1	54.188	34.913	.001
Seq x P	23	.769	.495	
Error	24	1.552		
Dominance	1	126.750	80.851	.001
Seq x Dom	23	1.783	1.137	
Error	24	1.568		
P x Dom	1	5.672	8.782	=.007
Seq x P x Dom	23	.552	.855	
Error	24	.646		
SOA	3	.328	.336	
Seq x SOA	69	1.080	1.105	
Error	72	.977		
P x SOA	3	.566	.494	
Seq x P x SOA	69	.959	.837	
Error	72	1.146		
Dom x SOA	3	.719	.698	
Seq x Dom x SOA	69	1.302	1.265	
Error	72	1.030		
P x Dom x SOA	3	2.280	2.045	
Seq x P x Dom x SOA	69	.863	.774	
Error	72	1.115		
P x Dom x SOA (lin)	1	5.251	4.558	=.043
Error	24	1.152		
P x Dom x SOA (curve)	2	.794	.724	
Error	48	1.096		

TABLE 17
COMBINED RESULTS OF THE RT AND ERROR ANALYSES FOR EXPERIMENT 3

SV	df	Reaction Time MS	Reaction Time F	Errors MS	Errors F
Between-subjects					
Lists (L)	3	2,231,884	1.889	.471	.821
Error	52	1,181,348			
Within-subjects					
Prime (C)	1	217,338	14.475**	.502	2.956
CL	3	54,781	3.648*	.075	.442
Error	52	15,015		.170	
SOA (I)	1	733,011	62.630**	.002	.013
IL	3	163,986	14.011**	.724	4.177*
Error	52	11,704		.173	
CI	1	31,482	2.688	.056	.238
CIL	3	18,243	1.560	.275	1.172
Error	52	11,711		.234	
Exemplar dom (E)	1	413,495	22.986**	.056	.238
EL	3	6,862	.381	.111	.702
Error	52	17,989		.234	
CE	1	2,051	.186	.109	.574
CEL	3	30,033	2.721	.221	1.159
Error	52	11,038		.191	
IE	1	46,424	3.412	.502	2.727
IEL	3	50,055	3.679	.245	1.329
Error	52	13,606		.184	
CIE	1	631	.057	.270	1.543
CIEL	3	10,152	.916	.105	.599
Error	52	11,085		.175	
Property dom (P)	1	527,555	24.088**	.181	.778
PL	3	18,852	.861	.099	.426
Error	52	21,901		.232	

TABLE 17 - continued

SV	df	Reaction Time MS	Reaction Time F	Errors MS	Errors F
CP	1	200,752	17.034**	.056	.308
CPL	3	35,191	3.144*	.406	2.240
Error	52	11,194		.181	
IP	1	54,417	5.137*	.020	.082
IPL	3	209,959	19.822**	.435	1.777
Error	52	10,592		.245	
CIP	1	691	.081	.020	.097
CIPL	3	7,062	.828	.379	1.827
Error	52	8,529		.207	
EP	1	80,183	8.023*	.984	5.126*
EPL	3	10,159	1.017	.155	.810
Error	52	9,994		.192	
CEP	1	10,710	1.142	.056	.378
CEPL	3	6,680	.712	.111	.751
Error	52	9,379		.148	
IEP	1	19,511	1.348	.002	.008
IEPL	3	64,069	4.428*	.212	.799
Error	52	14,470		.265	
CIEP	1	1,558	.200	.020	.127
CIEPL	3	6,658	.855	.519	3.274*
Error	52	7,790		.158	

*$p < .05$
**$p < .005$

Note: Although practice effects have been partitioned out of the data whose analysis is reported above, the effects of practice have not been reported in this table because they are of little theoretical interest.

APPENDIX D

RESULTS FOR FALSE ITEMS OF EXPERIMENT 3

TABLE 18

MEAN REACTION TIMES (IN MSEC) AND PERCENTAGE ERRORS (IN PARENTHESES) FOR THE FALSE ITEMS IN EXPERIMENT 3

SOA = 200 msec

Exemplar Dominance = Property Dominance =		High High	High Low	Low High	Low Low	Mean
Prime	Neutral	1259 (7.44)	1274 (8.93)	1248 (6.70)	1294 (5.36)	1269 (7.11)
	Category	1235 (8.18)	1260 (8.18)	1231 (6.70)	1246 (5.21)	1243 (7.07)
Priming Effect		24 (-0.74)	14 (0.75)	17 (0.00)	48 (0.15)	26 (0.04)

SOA = 600 msec

Exemplar Dominance = Property Dominance =		High High	High Low	Low High	Low Low	Mean
Prime	Neutral	1233 (8.63)	1233 (8.63)	1189 (4.02)	1237 (5.36)	1223 (6.66)
	Category	1190 (8.04)	1211 (8.18)	1169 (5.21)	1220 (6.10)	1198 (6.88)
Priming Effect		43 (0.59)	22 (0.45)	20 (-1.19)	17 (-0.74)	25 (-0.22)